



RESEARCH & DEVELOPMENT

NC Transportation Center of Excellence on Connected and Autonomous Vehicle Technology (NC-CAV)

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16. Abstract <i>Connected Autonomous Vehicles (CAVs)</i> are expected to create new opportunities by enhancing the mobility, safety, efficiency, reliability, affordability, and sustainability of transportation systems while rapidly disrupting traditional transportation technologies. This proposal brings together a strong and diverse team of researchers from North Carolina A&T State University (NCAT), North Carolina State University (NCSU), and University of North Carolina at Charlotte (UNCC) with the goal of establishing a multidisciplinary Center of Excellence in “Advanced Transportation Technologies” to investigate the adoption, utilization, and deployment of CAVs and their impacts on the transportation system in North Carolina and the nation. In addressing the solicitation, the proposed Center, NC-CAV, incorporated three interwoven research thrusts that achieve the stated goal, namely: Thrust 1: CAV Impacts; Thrust 2: CAV Infrastructure, and Thrust 3: CAV-UAV Emerging Applications. These research thrusts collectively aimed at achieving transformative objectives in the following ways: (1) Investigating the impacts of CAVs on North Carolina's transportation system (while explicitly accounting for mixed vehicle fleet with different levels of CAV adoption under different traffic situations) and associated revenue, (2) Assessing North Carolina's readiness for CAVs in traditional and emerging transportation infrastructure, (3) Developing and deploying CAVs and UAVs for advancing transportation systems, (4) Sustaining the Center's activities by attracting larger funding at the national level on advanced transportation systems, and (5) Developing an outreach program and a diverse workforce within the scope of the Center with the involvement of more graduate and undergraduate students, particularly those belonging to underrepresented groups.			
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EXECUTIVE SUMMARY

Connected Autonomous Vehicles (CAVs) are expected to create new opportunities by enhancing the mobility, safety, efficiency, reliability, affordability, and sustainability of transportation systems while rapidly disrupting traditional transportation technologies. This proposal brings together a strong and diverse team of researchers from North Carolina A&T State University (NCAT), North Carolina State University (NCSU), and University of North Carolina at Charlotte (UNCC) with the goal of **....establishing a multidisciplinary Center of Excellence in “Advanced Transportation Technologies” to investigate the adoption, utilization, and deployment of CAVs and their impacts on the transportation system in North Carolina and the nation.**

The NC-CAV Center incorporated three interwoven research thrusts that achieve the stated goal, namely: Thrust 1: CAV Impacts; Thrust 2: CAV Infrastructure, and Thrust 3: CAV-UAV Emerging Applications. These research thrusts collectively aimed at achieving transformative objectives in the following ways:

1. Investigating the impacts of CAVs on North Carolina’s transportation system (while explicitly accounting for mixed vehicle fleet with different levels of CAV adoption under different traffic situations) and associated revenue,
2. Assessing North Carolina’s readiness for CAVs in traditional and emerging transportation infrastructure,
3. Developing and deploying CAVs and UAVs for advancing transportation systems,
4. Sustaining the Center’s activities by attracting larger funding at the national level on advanced transportation systems, and
5. Developing an outreach program and a diverse workforce within the scope of the Center with the involvement of more graduate and undergraduate students, particularly those belonging to underrepresented groups.

These objectives were realized through innovative, cutting-edge, synergistic, interdisciplinary approaches built upon the existing facilities and strong foundation within leading research institutes and centers across North Carolina including the Autonomous Control and Information Technology (ACIT) Institute at NCAT, Institute for Transportation Research and Education (ITRE) at NCSU, USDOT University Transportation Center for Advanced Multimodal Mobility Solutions and Education (CammSE) at UNCC, TECHLAV Center of Excellence in Autonomy at NCAT, and their affiliated research laboratories. The proposed Center’s activities have led to deliverables that include analysis reports on the impacts of CAVs on the transportation system and associated revenue, roadmaps and strategic long-term planning reports about the required transportation infrastructure for CAVs, and the development and deployment of mixed transportation systems including manned vehicles, CAVs, and UAVs for transportation solutions and aerial traffic monitoring. Including NCDOT, Downtown Greensboro and Greensboro Department of Transportation served as the other public stakeholders for this project and provide equipment and logistics needed for a pilot program deployment of CAVs in its downtown district from the NCAT campus. These developments and deliverables will assist NCDOT and transportation policy/decision-makers to better understand and proactively plan for future developments and long-term trends in the deployment of CAVs for advanced transportation systems. Critically, this Center leveraged the ongoing CAV-related research at participating universities in concert with the center thrusts to competitively advance North Carolina’s transportation research on CAVs at the national level. This is done through the relationships developed in this Center, with NCDOT, and its national research partners such as the National Institute of Aerospace (NIA), the NASA Langley Research Center and industrial partners (including General Motors and National Instruments) in developing and deploying innovative CAV-UAV applications that address the needs of the State.

Contents

EXECUTIVE SUMMARY	5
List of Tables	14
List of Figures	18
1. Introduction	19
1.1 Introduction	19
1.2 Research Objectives	19
1.3 NC-CAV Approach and Organization	19
2. Research Findings under Thrust 1 (CAV Impacts on Traffic Intersection Capacity and Transportation Revenue)	21
2.1 Background	21
2.2 Task 1: Literature Review	22
2.3 Task 2: Identify Potential Intersections	22
2.4 Task 3: Design Scenarios for the Conduct of Simulation	22
2.5 Task 4: Use Simulations to Examine the Established Modeling Framework	23
2.6 Task 5: Develop Guideline on the Intersection Capacity Adjustments Considering Different Levels of CAV Market Penetration	23
2.6.1 Methods for Intersection Capacity Analysis:	23
2.6.1.1 Lane-level Capacity Analysis Method:	23
2.6.1.2 Intersection-level Capacity Analysis Method:	24
2.6.2 Adjustment Lookup Tables:	25
2.6.2.1 Lane-level Adjustment Factors:	25
2.6.2.2 Intersection-level adjustment factors:	25
2.6.3 Summary	26
2.7 Task 6: Conduct a Revenue Impact Analysis and Propose New Methods	26
2.7.1 Introduction	26
2.7.1.1 Current revenue sources	26
2.7.1.1.1 Motor Fuels Tax	26
2.7.1.1.2 Federal Funding	26
2.7.1.1.3 Highway Use Tax	27
2.7.1.1.3.1 Alternative Highway Use Tax	27
2.7.1.1.4 DMV Fees	28
2.7.1.1.4.1 Supplemental fee on electric vehicles	28
2.7.1.1.5 Other sources	28
2.7.1.2 Comparison to other states:	29
2.7.2 Revenue challenges	29
2.7.2.1 Changing patterns of car usage:	29
2.7.2.2 Electrification:	29
2.7.2.3 Decreased fee and HUT revenue:	30
2.7.2.4 Improving fuel economy:	30
2.7.3 Revenue options	32
2.7.3.1 Implementation of a Road User Charge:	32
2.7.3.1.1 Advantages	33
2.7.3.1.2 Challenges	33
2.7.3.2 Motor Fuels Tax reform:	33
2.7.3.2.1 Advantages	33
2.7.3.2.2 Challenges	33
2.7.3.3 Hypothecated sales tax:	34
2.7.3.3.1 Advantages	34
2.7.3.3.2 Challenges	34
2.7.3.4 Highway Use Tax reform:	34
2.7.3.4.1 Advantages:	34
2.7.3.4.2 Challenges:	35
2.7.3.5 Increased fee revenue:	35
2.7.3.5.1 Advantages:	35

2.7.3.5.2	Challenges:	35
2.7.3.5.3	Revenue projection:	35
2.7.3.6	Taxes on alternative fuels	35
2.7.3.6.1	Advantages:	35
2.7.3.6.2	Challenges:	35
2.7.3.7	Increased toll revenue	37
2.7.3.7.1	Advantages:	37
2.7.3.7.2	Challenges:	37
2.7.3.8	State appropriations:	37
2.7.3.8.1	Advantages:	37
2.7.3.8.2	Challenges:	37
2.7.3.9	Introduce a tax or fee on for-hire vehicle trips:	37
2.7.3.9.1	Advantages:	38
2.7.3.9.2	Challenges:	38
2.7.3.10	Transfer of facilities:	38
2.7.3.10.1	Advantages:	38
2.7.3.10.2	Disadvantages:	38
2.7.3.11	Other mechanisms	38
2.7.3.11.1	Hypothecated income tax:	38
2.7.3.12	New taxes or fees on non-motorists:	38
2.7.3.13	Tire tax:	38
2.7.4	Conclusion:	39
3.	Research Findings under Thrust 2 (Assessing North Carolina Readiness for CAVs in Traditional and Emerging Infrastructure Needs)	40
3.1	Background	40
3.2	Task 1: Literature Review	41
3.2.1	Traditional Infrastructure Impacts:	41
3.2.1.1	Geometry:	41
3.2.1.2	Signs and Markings:	42
3.2.1.3	Traffic Signals:	44
3.2.2	Emerging Infrastructure Impacts	46
3.2.2.1	Advanced Intelligent Transportation Systems (ITS):	46
3.2.2.2	V2X and CV Testbeds	46
3.2.2.2.1	V2X:	46
3.2.2.2.2	V2I:	47
3.2.2.2.3	CV Testbeds:	49
3.2.3	Communications:	52
3.2.4	Cybersecurity:	53
3.3	Summary	54
3.4	Task 2: Analysis of Existing Infrastructure and Maintenance Programs to Support CAV Deployment	55
3.5	Methodology	55
3.6	Survey Results	56
3.6.1	Demographics	56
3.6.2	Descriptive Statistics	56
3.6.2.1	CAV Impacts on Various Units of a Public Agency:	58
3.6.2.2	Public Agencies' Readiness to Accommodate CAVs:	58
3.6.2.3	Public Agencies' Strategic Planning for CAVs:	60
3.6.2.4	Public Agencies' Training Needs to Accommodate CAVs:	60
3.6.3	Summary of Descriptive Statistics:	61
3.6.4	Opinion Comparison: Hypothesis Tests:	61
3.6.4.1	CAV Impacts on Public Agencies:	61
3.6.4.2	Public Agencies' Readiness to Accommodate CAVs:	62
3.6.4.3	Public Agencies' Strategic Planning for CAVs:	62
3.6.4.4	Public Agencies' Training Needs to Accommodate CAVs:	63

3.6.4.5	Summary:	63
3.7	Task 3: Establish Low-Latency Edge Computing Infrastructure Recommendations for North Carolina	64
3.7.1	Signal and Communication Setups:	65
3.7.2	Problem Formulation:	66
3.7.3	The Development of DL-based Spectrum Reconstruction:	66
3.7.3.1	Deep Learning Model Architecture:	67
3.7.3.2	Loss Functions:	67
3.7.4	A New C-V2X Platform and Numerical Results:	67
3.7.4.1	Transportation module:	67
3.7.4.2	Communication module:	68
3.7.4.3	Data set generation:	68
3.7.4.4	Performance Metrics:	69
3.7.4.5	Performance Comparison:	69
3.7.5	Conclusion:	69
3.8	Task 4: Recommend Program Enhancements to Further NC Readiness for CAVs	69
4.	Research Findings under Thrust 3 (Developing and Implementing CAV-UAV Collaboration for Advancing the Transportation Systems)	72
4.1	Background	72
4.2	Task 1: Literature Review	72
4.3	Task 2: Development of Cooperative Control of Heterogeneous CAVs for On-Demand Mobility	73
4.3.1	Problem Statement:	74
4.3.1.1	Notations and Definitions:	74
4.3.1.2	Constrained Profit Optimization:	75
4.3.2	Proposed Method:	75
4.3.3	Experimental Study:	76
4.3.3.1	Simulation Details:	76
4.3.3.2	Algorithm Comparison:	76
4.3.3.3	Results:	76
4.3.3.4	Time Complexity Analysis:	77
4.3.4	Conclusion:	77
4.4	Task 3: Development of a Testbed for Cooperative Control of CAVs/UAVs	78
4.4.1	Development of hardware-in-the-loop Simulator:	78
4.4.2	Development of a CAV testbed of autonomous vehicles:	79
4.4.2.1	Installation, operationalizing and testing of hardware components:	79
4.4.2.2	Development and testing of software components:	79
4.4.2.3	Installation, operationalizing, and testing of communication devices:	79
4.4.2.4	Integration of hardware and software components:	80
4.4.3	Development of an in-house AV testbed:	80
4.4.4	Enhancing the perception and safety of CAVs:	81
4.5	Task 4: Aerial traffic monitoring using CAVs	82
4.5.1	UAV-based Traffic Monitoring Framework:	83
4.5.2	Automation of Data Processing:	85
4.5.3	Conclusion:	90
4.6	Task 5: Field experiments and testing	90
5.	Outreach, Dissemination, and Workforce Development Activities under NC-CAV Center	93
5.1	Outreach and Workforce Development Activities under NC-CAV Center	93
5.1.1	NC-CAV: Sustainability Activities:	95
5.1.2	NC-CAV Center Activities for the Engagement of Stakeholders and Industrial Partners	97
5.2	Dissemination of Research Findings	98
5.2.1	NC-CAV Seminar Series:	98
5.3	Publications and Reports	100
6.	Conclusions	103
A.	Comprehensive review of the state-of-the-practice of CAV technology	107
A.1	Overview of Connected Autonomous Vehicles	107

A.1.1	CAV Stakeholders:	108
A.1.2	CAV Use Cases:	108
A.2	CAV Impacts: A statistical Perspective	109
A.3	CAV Sectors' State of The Art	111
A.3.1	Current State of Autonomous Vehicle Technology:	111
A.3.1.1	Autonomous Vehicle Development: Research Platforms:	111
A.3.1.2	Autonomous Vehicle Development: The Commercialized Efforts:	111
A.3.2	CAV Road Infrastructure:	111
A.3.3	CAV Communications and Computation Infrastructure:	113
A.3.3.1	Latest Practice on CAV Communication Infrastructure:	113
A.3.3.2	Intelligent Vehicular Networked Edge Infrastructure:	114
A.3.3.3	Data-Driven CAV Service Management & Orchestration:	114
A.4	Current State of CAV Practice	115
A.5	Future Challenges for Development and Deployment of CAVs	115
A.6	Conclusions	116
B.	Thrust 1: Impact of Connected and Autonomous Vehicles (CAVs) on North Carolina's Transportation System and Associated Revenue	118
B.1	LITERATURE REVIEW	118
B.1.1	Introduction	118
B.1.2	Connected and Autonomous Vehicles Concepts and Potential Benefits	118
B.1.2.1	Connected Vehicles (CVs)	118
B.1.2.2	Autonomous Vehicles (AVs)	118
B.1.2.3	Connected and Autonomous Vehicles (CAVs)	119
B.1.3	Deployment of and Market Forecast for AVs:	121
B.1.3.1	Deployment of the Autonomous Vehicles	121
B.1.3.2	Connected and Autonomous Vehicles (CAVs)	123
B.1.4	Traffic Flow Controls of CAVs	123
B.1.4.1	Longitudinal Movement Control of CAVs	124
B.1.4.2	Latitudinal Movement Control of CAVs	127
B.1.5	Control Strategy for CAVs at Intersections	127
B.1.5.1	Signalized Intersection Control	127
B.1.5.2	Autonomous Intersection Control	128
B.1.6	Intersection Capacity Analysis Methods	129
B.1.6.1	Empirical Based Methods	129
B.1.6.2	Simulation Based Methods	129
B.1.7	Intersection Modeling Scenarios and Parameters	132
B.1.8	Summary	134
B.2	IDENTIFYING POTENTIAL INTERSECTIONS	135
B.2.1	Introduction	135
B.2.2	Typical Isolated Intersection Scenario	135
B.2.2.1	Intersection Layout	135
B.2.2.2	Pre-timed Signal Schemes	135
B.2.2.3	Potential Traffic Demands	135
B.2.3	Potential Intersections in North Carolina	136
B.2.3.1	One isolated intersection in Charlotte, NC	136
B.2.3.2	Two adjacent intersections in Greensboro, NC	137
B.2.4	Summary	137
B.3	DESIGNING SCENARIOS FOR CONDUCTING SIMULATION	137
B.3.1	Introduction	137
B.3.2	Empirical Method for Intersection Capacity Analysis	139
B.3.2.1	Quick-Estimation Method	139
B.3.2.2	Intersection Capacity Calculation	139
B.3.3	Microscopic Simulation Model for Human Driving Vehicles	140
B.3.3.1	Traffic Simulation Model for Human Driving Vehicles	141

B.3.3.2	Basic Parameters for Specific Traffic Simulation Models	142
B.3.4	Scenarios for Intersections:	142
B.3.4.1	Scenarios for Typical Isolated Intersection	143
B.3.4.2	Scenarios for Intersections in North Carolina	145
B.3.5	Summary	145
B.4	USING SIMULATIONS TO EXAMINE THE ESTABLISHED MODELING FRAMEWORK	146
B.4.1	Introduction	146
B.4.2	Capacity Analysis for Typical Isolated Intersection	146
B.4.2.1	Intersection Capacity Analysis at the Lane Level	146
B.4.2.2	Intersection Capacity Analysis at the Intersection Level	151
B.4.3	Impacts of CAV Penetration Rates under Fixed Traffic Demands	167
B.4.3.1	Hypothetical isolated Intersection	167
B.4.3.2	Isolated Intersection in Charlotte, NC	169
B.4.3.3	Two Adjacent Intersections in Greensboro, NC	171
B.4.4	Summary	173
B.5	SUMMARY AND CONCLUSIONS	173
C.	GCN-CNVPS: Novel Method for Cooperative Neighboring Vehicle Positioning System Based on Graph Convolution Network	176
C.1	Introduction	176
C.2	System Setup and Problem Formulation	177
C.2.1	System Setup:	177
C.2.2	Sensor Configuration:	178
C.2.2.1	GPS:	178
C.2.2.2	Radars:	178
C.2.2.3	RSSI:	178
C.2.3	Problem Statement:	178
C.3	Development of DL-based Localization Algorithms	179
C.3.1	Overview:	179
C.3.2	Architecture of the Proposed MLP-CNVPS:	179
C.3.3	Architecture of the Proposed LSTM-CNVPS:	180
C.3.4	Architecture of the Proposed GCN-CNVPS:	181
C.3.5	Training Method:	182
C.4	Simulation Results and Discussion	183
C.4.1	Data Generation:	183
C.4.2	Performance Analysis with Single Time-Slot Measurements:	183
C.4.3	Performance Analysis with Multiple Time-Slot Measurements:	183
C.4.4	Scalability of Proposed Algorithms:	185
C.4.5	Training overhead of Different DL-based CNVPS algorithms:	186
C.5	Conclusion	186
D.	Dynamic Power Allocation and Virtual Cell Formation for Throughput-Optimal Vehicular Edge Networks in Highway Transportation	188
D.1	Introduction	188
D.2	System Model and Problem Formulation	189
D.2.1	Software-Defined System Model:	189
D.2.2	Road Model and Node Distributions:	190
D.2.3	Software-Defined Vehicle-to-Infrastructure Communication:	190
D.2.4	User-Centric Dynamic Cell Formation:	191
D.3	Reinforcement Learning-Based Vehicular Edge Slicing Mechanism	192
D.3.1	State:	192
D.3.2	Action:	192
D.3.3	Reward:	192
D.3.4	Single Agent Reinforcement Learning (SARL):	193
D.3.5	Multi-agent Reinforcement Learning (MARL):	193
D.3.6	Distributed SARL with Multi-agent Learning (SARL-MARL Collaboration):	193

D.4	Performance Evaluation	194
D.5	Conclusion	196
E.	Eco-Vehicular Edge Networks for Connected Transportation: A Distributed Multi-Agent Reinforcement Learning Approach	200
E.1	Introduction	200
E.2	Software-Defined Vehicular Edge Networks	201
E.2.1	Software-Defined System Model:	201
E.2.2	SD-V2I Communication Model:	202
E.2.3	User-Centric Dynamic Cell Formation:	202
E.3	Energy-Efficient Resource Slicing at Edges: A Reinforcement Learning Approach	203
E.3.1	Single Agent Reinforcement Learning (SARL):	203
E.3.2	Distributed Multi-Agent RL (D-MARL):	204
E.4	Performance Evaluation	205
E.4.1	Average Energy-Efficiency Comparisons	205
E.4.2	Impact of the Reliability Constraint:	206
E.4.3	Impact of the Coverage Radius:	207
E.4.4	User Fairness:	207
E.5	Conclusion	208
F.	CAV Revenue Impact Analysis and Mitigation Strategies	211
F.1	Introduction	211
F.1.1	Current revenue sources	211
F.1.1.1	Motor Fuels Tax	211
F.1.1.2	Federal Funding	211
F.1.1.3	Highway Use Tax	211
F.1.1.4	Alternative Highway Use Tax	211
F.1.1.5	DMV Fees	213
F.1.1.6	Supplemental Fee on Electric Vehicles	213
F.1.1.7	Other Sources	213
F.2	Comparing to Other States	213
F.3	Revenue challenges	213
F.3.1	Changing patterns of car usage	213
F.3.2	Electrification	214
F.4	Decreased fee and HUT revenue	215
F.4.1	Improving fuel economy	215
F.5	Revenue options	217
F.5.1	Implementation of a Road User Charge	217
F.5.1.1	Advantages	217
F.5.1.2	Challenges	217
F.5.2	Motor Fuels Tax reform	217
F.5.2.1	Advantages	218
F.5.2.2	Challenges	218
F.5.3	Hypothecated sales tax	218
F.5.3.1	Advantages	218
F.5.3.2	Disadvantages	218
F.5.4	Highway Use Tax reform	218
F.5.4.1	Advantages	219
F.5.4.2	Challenges	219
F.5.5	Increased fee revenue	219
F.5.5.1	Advantages	219
F.5.5.2	Challenges	219
F.5.5.3	Revenue projection	219
F.5.6	Taxes on alternative fuels	219
F.5.6.1	Advantages	219
F.5.6.2	Challenges	219

F.5.7	Increased toll revenue	221
F.5.7.1	Advantages	221
F.5.7.2	Challenges	221
F.5.8	State appropriations	221
F.5.8.1	Advantages	221
F.5.8.2	Challenges	221
F.5.9	Introduce a tax or fee on for-hire vehicle trips	221
F.5.9.1	Advantages	221
F.5.9.2	Disadvantages	221
F.5.10	Transfer of facilities	222
F.5.10.1	Advantages	222
F.5.10.2	Disadvantages	222
F.5.11	Other mechanisms	222
F.5.11.1	Hypothecated income tax	222
F.5.12	New taxes or fees on non-motorists	222
F.5.13	Tire tax	222
F.6	Conclusion	223
G. :	Develop Guideline on the Intersection Capacity Adjustments Considering Different Levels of CAV	
	Market Penetration	226
G.1	Introduction	226
G.2	Methods for Intersection Capacity Analysis	226
G.2.1	Lane-level Capacity Analysis Method	226
G.2.2	Intersection-level Capacity Analysis Method	227
G.3	Adjustment Lookup Tables	227
G.3.1	Lane-level Adjustment Factors	228
G.3.2	Intersection-level adjustment factors	228
G.4	Summary	229
	Bibliography	230

List of Tables

Table 1	Adjustment factors for saturation headway and saturation flow rate for each lane group under different MPRs of CAVs	25
Table 2	Traffic performance under saturated traffic flow with different MPRs of CAVs	26
Table 3	State-sourced highway revenues, FY2018	29
Table 4	Stopping sight distance under various perception-reaction time and maximum deceleration rates .	42
Table 5	Stopping sight distance under various perception-reaction time and maximum deceleration rates .	43
Table 6	V2I Messages by Application and Message Handler	49
Table 7	<i>Demographics of the respondents</i>	56
Table 8	<i>Average scores on resource availability</i>	60
Table 9	Hypothesis Testing Results on Unit Impact Caused by Connected Vehicles. Note: STD = standard deviation and N = sample size.	62
Table 10	Hypothesis Testing Results on Unit Impact Caused by Autonomous Vehicles	62
Table 11	Hypothesis Testing Results on Unit Readiness to CAVs	62
Table 12	Hypothesis Testing Results on Resource Availability to Accommodate CAVs	63
Table 13	Hypothesis Testing Results on Trainings Needed to Accommodate CAVs	63
Table 14	Comparison of spectrum reconstruction in different bands with SNR = 30 dB and compression rate = 0.125	69
Table 15	System Parameter Settings (default values in bold).	76
Table 16	The performance of the proposed model	90
Table 17	Safety benefits and maturity of connected vehicle technologies	119
Table 18	Outline of five automation levels (NHTSA, 2016) [226]	120
Table 19	Benefits and maturity of autonomous vehicle technologies	121
Table 20	Autonomous technology project proposed by Volvo	122
Table 21	Longitudinal movement control model for AVs and CAVs	125
Table 22	Summaries of empirical-based methods on intersection capacity analysis	130
Table 23	Summaries of capacity analysis studies of CAVs under 100% market penetrate rate	131
Table 24	Summaries of capacity studies of CAVs under mixed traffic environment	132
Table 25	Summaries of other performance measures of CAVs under mixed traffic environment	133
Table 26	Summaries of intersection modeling scenarios with CAVs	134
Table 27	Basic parameters in each car-following model	142
Table 28	Specific factors for traffic simulation models	143
Table 29	Assumed through vehicle equivalents in the East Boundary	143
Table 30	Critical lane volume in each phase	144
Table 31	Calculated through vehicle equivalents in the East Boundary	144
Table 32	Traffic volume of each traffic movement at the isolated intersection	145
Table 33	Saturation headway for each lane under different MPRs of CAVs	150
Table 34	Adjustment factors for saturation headway and saturation flow rate for each lane group under different MPRs of CAVs	151
Table 35	Intersection system performance under different traffic demands	153
Table 36	Intersection system performance under 10% MPRs of CAVs	154
Table 37	Intersection system performance under 20% MPRs of CAVs	155
Table 38	Intersection system performance under 30% MPRs of CAVs	156
Table 39	Intersection system performance under 40% MPRs of CAVs	157
Table 40	Intersection system performance under 50% MPRs of CAVs	158
Table 41	Intersection system performance under 60% MPRs of CAVs	159
Table 42	Intersection system performance under 70% MPRs of CAVs	160
Table 43	Intersection system performance under 80% MPRs of CAVs	161
Table 44	Intersection system performance under 90% MPRs of CAVs	162
Table 45	Intersection system performance under 100% MPRs of CAVs	163
Table 46	Traffic performance under saturated traffic flow with different MPRs of CAVs	165

Table 47	Performance Comparisons: $\gamma_i^{min} = 10 \text{ dB}$, AP Coverage Radius = 250 m	205
Table 48	State-sourced highway revenues, FY2018	213
Table 49	Adjustment factors for saturation headway and saturation flow rate for each lane group under different MPRs of CAVs	228
Table 50	Traffic performance under saturated traffic flow with different MPRs of CAVs	228

List of Figures

Figure 1	Current NCDOT funding sources	27
Figure 2	Federal gasoline tax vs CPI inflation, 1993-present	28
Figure 3	NC electric vehicle adoption forecast	30
Figure 4	Annual Motor Fuels Tax revenue by VMT as MPG (US) improves	31
Figure 5	Breakeven analysis: Current electric vehicle fee vs MFT revenue	31
Figure 6	MFT revenue at 15,000 VMTs per year as MPG improves	32
Figure 7	Projected EV supplemental registration fee revenue at various rates	36
Figure 8	EV supplemental fee vs lost MFT, 2025	36
Figure 9	Comparison of sag vertical curve for current design standards and automated vehicles Source: [146]	42
Figure 10	Width of longitudinal pavement marking in the U.S.	44
Figure 11	Illustration of Infrastructure to Vehicle (I2V) communications Photo Source: [289]	45
Figure 12	Illustration of Cooperative traffic control in the neighborhood intersection Source: [209]	45
Figure 13	Architecture of cooperative and intelligent transportation Source: [312]	47
Figure 14	Structure of V2X communication	48
Figure 16	Cyber attack threats in the autonomous vehicle	55
Figure 17	<i>Location of the respondents in the continental US</i>	57
Figure 18	<i>Years of experience of the respondents in the field of CAVs</i>	57
Figure 19	<i>Distribution of responses concerning the impact of connected vehicles</i>	58
Figure 20	<i>Distribution of responses concerning the impact of autonomous vehicles</i>	59
Figure 21	<i>Distribution of responses concerning the status quo of units to accommodate CAVs</i>	59
Figure 22	<i>: Distribution of responses concerning the resource availability in preparation for the accommodation of CV, AV, CAV</i>	60
Figure 23	<i>Distribution of responses concerning the training needs in preparation for the accommodation of CV, AV, CAV</i>	61
Figure 24	The Illustration of the proposed vehicular communication platform. In the proposed platform, transportation module and communication module are integrated to generate realistic data for verification of vehicular communication algorithms. To be more specific, when a geographical information is imported, transportation module will create realistic traffic on it, then wireless communications will be simulated. As a result, the proposed platform can be used to assess the achieved performance of various vehicular communication algorithms in real scenarios.	64
Figure 25	The detailed process of the transportation module: Using the transportation module, realistic traffic will be created in region of interest and the trajectories of vehicles will be recorded for further use.	66
Figure 26	The detailed process of the communication module: In each time step, based on the realistic trajectories data and communication system settings, wireless connections will be created and the detailed information is also provided in our platform.	68
Figure 27	CAVs offer cooperative functionalities to optimally manage resources and demands, and safety in the transportation system.	73
Figure 28	Schematic overview of vehicle dispatch logic.	75
Figure 29	Comparison of performance for varying maximum waiting time.	77
Figure 30	Comparison of performance for varying vehicle capacity.	77
Figure 31	Hardware-in-the-loop simulator setup.	78
Figure 32	Lidar/Pointcloud map for localization.	79
Figure 33	Communication of CAVs.	80
Figure 34	Autoware software architecture.	80
Figure 35	Development of a Testbed for Cooperative Control of CAVs with Gem e2 Car	81

Figure 36	Detection comparisons: The top row represents the input images. Then, the middle row indicates the corresponding semantic map of input images. Finally, the bottom row shows the ground truth, baseline detection, and detection with the fusion mechanism. Green, blue, and red color bounding boxes represent ground truth, baseline detection, and improvement with fusion, respectively.	82
Figure 37	UAV based traffic monitoring conceptual framework.	84
Figure 38	Traffic parameter specific automation process flowchart	85
Figure 39	Example of vehicle trajectory plot	86
Figure 40	DJI's GEO System flying zone delineation for the I40 study area [76]	87
Figure 41	DJI's GEO System flying zone delineation for the I40 study area [76]	88
Figure 42	Auto-vehicle counting algorithm schematics	89
Figure 43	(a) Location of sensors installed on the CAV testbeds and their (b) safety cocoon	91
Figure 44	(a) standard deviation errors and (b) waypoint creation using GPS localization	91
Figure 45	(a) subsection of global map and (b) what the lidar currently perceives	92
Figure 46	Major stakeholders in the CAV space.	108
Figure 47	Proposed roadside infrastructure for CAVs: 1. Traffic Control Devices (TCDs), 2. Vehicle Communication Devices 3. Roadside Units (RSUs). CAVs can communicate with RSUs and TCDs using vehicle communication protocol. RSUs and vehicles are connected to a remote server through internet. [6].	112
Figure 48	Prediction of sales for new passenger cars (in millions) (PTOLEMUS, 2017) [256]	123
Figure 49	Prediction of sales, travel, and fleet proportion rates of AVs (Litman, 2020) [185]	124
Figure 50	Pre-timed signal control scheme	127
Figure 51	Actuated signal control scheme	128
Figure 52	Layout of the hypothetical isolated four-way intersection	135
Figure 53	Potential signal phase of the intersection	136
Figure 54	Isolated intersection in the city of Charlotte, NC	136
Figure 55	Two adjacent intersections in Greensboro, NC	137
Figure 56	Layout of the first intersection (Friendly Ave. & Murrow Blvd.)	138
Figure 57	Layout of the second intersection (Market St. & Murrow Blvd.)	138
Figure 58	Illustration of the Quick Estimation Method framework for capacity estimation	139
Figure 59	Pre-timed signal scheme for the isolated intersection	146
Figure 60	Traffic volume of each movement at the first intersection (Friendly Ave. & Murrow Blvd.)	147
Figure 61	Traffic volume of each movement at the second intersection (Market St. & Murrow Blvd.)	148
Figure 62	Pre-timed signal schemes for two adjacent intersections	149
Figure 63	Headway adjustment factors under different MPRs of CAVs	151
Figure 64	Saturation flow rate adjustment factors under different MPRs of CAVs	152
Figure 65	Traffic throughput with all human drive vehicles	152
Figure 66	Traffic throughput under 10% MPRs of CAVs	154
Figure 67	Traffic throughput under 20% MPRs of CAVs	155
Figure 68	Traffic throughput under 30% MPRs of CAVs	156
Figure 69	Traffic throughput under 40% MPRs of CAVs	157
Figure 70	Traffic throughput under 50% MPRs of CAVs	158
Figure 71	Traffic throughput under 60% MPRs of CAVs	159
Figure 72	Traffic throughput under 70% MPRs of CAVs	160
Figure 73	Traffic throughput under 80% MPRs of CAVs	161
Figure 74	Traffic throughput under 90% MPRs of CAVs	162
Figure 75	Traffic throughput under 100% MPRs of CAVs	163
Figure 76	Traffic waiting time per simulation step	164
Figure 77	Traffic CO2 emission per simulation step	164
Figure 78	Traffic fuel consumption per simulation step	165
Figure 79	Traffic cumulative throughput	166
Figure 80	Traffic throughput under different MPRs of CAVs	166

Figure 81	Maximum throughput under different MPRs of CAVs	167
Figure 82	Total CO2 emission of the saturated traffic flow with different MPRs of CAVs	167
Figure 83	Total fuel consumption of the saturated traffic flow with different MPRs of CAVs	168
Figure 84	Total waiting time of the saturated traffic flow with different MPRs of CAVs	168
Figure 85	Traffic demand conditions of the intersection with different MPRs of CAVs	169
Figure 86	Impacts of CAV penetration rates on the total waiting time under different traffic demand levels .	170
Figure 87	Three traffic demand ranges with different CAV impact trends on the total waiting time for the hypothetical isolated intersection	171
Figure 88	Layout of the isolated intersection in the city of Charlotte, NC	171
Figure 89	Impacts of CAV penetration rates on the total waiting time of the isolated intersection under different traffic demand levels	172
Figure 90	Layout of two adjacent intersections in Greensboro, NC	172
Figure 91	Impacts of CAV penetration rates on the total waiting time of the two-adjacent intersections under different traffic demand levels	173
Figure 92	The considered scenario of cooperative vehicle localization through V2V. V2V communication is used to transmit additional information acquired from on-board sensors for the use of GPS refinement. The information is arranged in a specific format and fed into the DL-based CNVPS algorithm, generating GPS-refined results.	177
Figure 93	Illustration of the proposed model structures under a multiple time-slot condition.(a) MLP-CNVPS: All input data from multiple time slots are fed into the model directly without further pre-processing. (b) LSTM-CNVPS: Input data from multiple time slots are separated and fed into the model in different time slots to emphasize the temporal correlation. (c) GCN-CNVPS: Using the special kernel design of a GCN, the adjacency matrix is used to describe the spatial correlation of input data under the graph structure, and to achieve a superior performance, the temporal and spatial correlation in the input feature matrix will be simultaneously emphasized. .	180
Figure 94	(a) Error mean versus scenarios and (b) error standard deviation versus scenario performance with $N = 5$ and $T_c = 1$	184
Figure 95	Error mean versus time slot performance under (a) free space, (b) suburban, and (c) urban scenarios in straight-through mode with $N = 5$. (d)–(f) Plots of the same for the standard deviation of the error.	184
Figure 96	Error mean versus time slot performance under (a) free space, (b) suburban, and (c) urban scenarios in lane change mode with $N = 5$. (d)–(f) Plots of the same for the standard deviation of the error.	184
Figure 97	Error mean versus time slot performance under (a) free space, (b) suburban, and (c) urban scenarios in straight-through mode with $N = 10$. (d)–(f) Plots of the same for the standard deviation of the error.	185
Figure 98	Error mean versus time slot performance under (a) free space, (b) suburban, and (c) urban scenarios in lane change mode with $N = 10$. (d)–(f) Plots of the same for the standard deviation of the error.	185
Figure 99	comparison of training overhead of different DL-based CNVPS algorithms.	186
Figure 100	User-centric vehicular edge networking.	189
Figure 101	Performance comparisons: AP coverage radius = 250 m, $\gamma_i^{min} = 10$ dB.	195
Figure 102	Impact of the SINR threshold.	197
Figure 103	Impact of the coverage radius of the access point.	198
Figure 104	Energy-efficient user-centric vehicular edge network.	201
Figure 105	Simulation environment	205
Figure 106	Probability of success for different SINR threshold when AP coverage radius is 250 m	206
Figure 107	Average EE for different SINR threshold when AP coverage radius is 250 m	207
Figure 108	Probability of success for different AP coverage radius when SINR threshold is 10 dB	207
Figure 109	Average EE for different AP coverage radius when SINR threshold is 10 dB	208
Figure 110	User fairness: AP coverage radius 250, SINR threshold 10 dB	208

Figure 111Current NCDOT funding sources	212
Figure 112Federal gasoline tax vs CPI inflation, 1993-present	212
Figure 113NC electric vehicle adoption forecast	214
Figure 114Annual Motor Fuels Tax revenue by VMT as MPG (US) improves	215
Figure 115Breakeven analysis: Current electric vehicle fee vs MFT revenue	216
Figure 116MFT revenue at 15,000 VMTs per year as MPG improves	216
Figure 117Projected EV supplemental registration fee revenue at various rates	220
Figure 118EV supplemental fee vs lost MFT, 2025	220

Chapter 1 Introduction

1.1 Introduction

North Carolina is the 10th fastest growing state in the nation. Its population is projected to increase by two million over the next 20 years, reaching nearly 13 million people. Most of this growth will occur in urban areas, necessitating greater transportation system capacity and technology implementation. The transportation industry is undergoing major revolutionary changes that promise increased capacity, reliability, affordability, and sustainability. Major achievements have been made in autonomous vehicle and computing technologies, and communication platforms are ready to support Connected Autonomous Vehicles (CAVs). These changes will disrupt traditional transportation technologies while creating new opportunities, benefiting the society through increased mobility, safety, accessibility, and reliability. In order to be better prepared for these transformative changes, several major questions need to be addressed: How will the transportation system look like with the deployment of CAVs and what are their emerging applications? What are the infrastructure needs for CAV technologies? What are the impacts of CAVs on North Carolina's transportation system, the users, and the associated revenue? This proposal is to establish a Center of Excellence on Connected Autonomous Vehicles (NC-CAV) to address these research questions and investigate the impacts of and challenges for deployment of CAVs.

1.2 Research Objectives

Aligned with the NCDOT's mission, the goal of this proposal was to establish NC-CAV as a multidisciplinary Center of Excellence in "Advanced Transportation Technologies" to investigate the adoption, utilization, and deployment of CAVs and their impacts on the transportation system in North Carolina and the nation. This will be achieved by seeking long-term view and cutting-edge multidisciplinary approaches to meet transformative objectives including: achieving the following objectives:

- **Objective 1:** Investigating the impacts of CAVs on the North Carolina's current transportation system (while explicitly accounting for mixed vehicle fleet with different levels of CAV adoption under different traffic situations) and an assessment of the fiscal impacts that CAVs would impose on North Carolina and its communities.
- **Objective 2:** Assessing North Carolina's readiness for CAVs, investigating the required changes to the existing transportation infrastructure needs to support CAVs, and to explore emerging technologies that can support CAV deployment
- **Objective 3:** Developing and implementing cooperative control techniques for CAVs and UAVs and exploring their emerging applications via development of prototypes and analysis of multiple use cases.
- **Objective 4:** Sustaining the Center's activities by attracting larger funding at the national level for advanced transportation systems.
- **Objective 5:** Developing an outreach program and a diverse and better-prepared workforce with more graduate and undergraduate students, particularly from underrepresented groups, across the three participating institutions, by exposing them to advanced CAV–UAV transportation technologies.

1.3 NC-CAV Approach and Organization

To achieve NC-CAV goals and objectives listed in the previous section, we conducted research on CAVs through three interwoven thrusts as listed below:

Thrust 1: CAV Impacts

Lead: Wei Fan (UNCC)

Co-Leads: Ali Hajbabaie (NCSU), Daniel Findley (NCSU) **Other Members:** Steve Bert (NCSU), Ryan Hassett (NCSU), Nick Norboge (NCSU), Steven Jiang (NCAT)

Scope: Thrust 1 researchers investigated the impacts of CAV technologies on the current transportation system's performance, in particular on intersection capacity adjustments while explicitly accounting for mixed vehicle fleet with different levels of CAV adoption. Within this Trust we also assessed the fiscal revenue impacts of the transition

to CAVs on North Carolina's cities, towns, and households. The achieved results under this thrust are presented in Chapter 2 of this report.

Thrust 2: CAV Infrastructure Lead: Shoaib Samandar (NCSU) **Co-Leads:** Shih-Chun Lin (NCSU), Thomas Chase (NCSU), John Kelly (NCAT), Abdollah Eroglu (NCAT) **Other Members:** Abdollah Eroglu (NCAT) **Scope:** Under Thrust 2, researchers analyzed the readiness of the existing transportation infrastructure and maintenance programs to support CAV deployment and will investigate the emerging infrastructure required for the adoption of future CAV technologies. The achieved results under this thrust are presented in Chapter 3 of this report.

Thrust 3: CAV-UAV Emergent Applications Lead: Abdollah Homaifar (NCA&T) **Co-Leads:** Ali Karimoddini (NCA&T), Nagui Roupail (NCSU), Chris Cunningham (NCSU) **Other Members:** Leila Hashemi (NCA&T), Wei Fan (UNCC) **Scope:** Under Thrust 3, researchers developed and validated cooperative control techniques for CAVs and UAVs. In particular, Thrust 3 developed a cooperative control techniques for On-Demand mobility applications, prototyped a testbed of a network of CAVs to implement emergent applications of CAVs, and explored the application of UAVs for transportation systems such as aerial traffic monitoring. The achieved results under this thrust are presented in Chapter 4 of this report.

Chapter 2 : Research Findings under Thrust 1 (CAV Impacts on Traffic Intersection Capacity and Transportation Revenue)

2.1 Background

In the past decades, emerging technologies that could assist or automatically control the driving process of traditionally human-driven vehicles have drawn great interest from researchers and engineers. With the development of Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) communication technologies, connected and autonomous vehicles (CAVs) could make driving-informed decisions based on multi-source data, such as the speed/location of the surrounding vehicles and the signal timing schemes of surrounding intersections. The requirement of the time gap for successive vehicles could also be sharply decreased, and this could significantly change the car-following behaviors and affect the performance of the transportation systems. However, it is expected to have a long transition period during which human driven vehicles (HDVs) and intelligent vehicles will coexist [278]. Hence, research on the impacts of CAV technologies and the mixed flow of HDVs and CAVs is needed.

CAVs will have a profound influence on the performance of the currently used and future transportation system, especially for the intersection that has complex traffic conditions. Several proposed intersection control systems require a modification of the existing intersections, particularly for high market penetration rates (MPRs) of Autonomous Vehicles (AVs) or Connected Vehicles (CVs) [18, 80]. Reconstruction of those intersections or installing the V2I equipment would take a long time. For example, the autonomous intersection management (AIM) system replaces signals with a reservation-based central control system. For this purpose, the AIM requires more than a 90% MPR of the CAVs [80]. However, there is still a long way to go for intelligent vehicles to be fully applicable in currently used traffic environments. Meanwhile, currently used Highway Capacity Manual (HCM) methods do not explicitly consider the impacts of CAVs on the transportation system. Evaluating the capacity of intersections under the impacts of CAVs is becoming a critical issue to be resolved for transportation planners and engineers. Consequently, new guidelines for estimating the capacity of intersections, including the consideration of CAV involvement in mixed traffic conditions, need to be established. Moreover, research needs to analyze the impacts of the CAV MPRs on the intersection capacity and modify the intersection capacity adjustment factors for engineering applications. Therefore, one important product of this research will be an evaluation of how CAVs will influence our current transportation system's performance, along with the provision of an in-depth analysis on intersection capacity adjustments considering varying levels of CAV adoption under different traffic situations.

In addition to capacity improvements, CAV technology also has the potential to significantly change the way we finance our transportation system. CAVs will impact motor fuel taxes, sales and use taxes, toll receipts, moving violation fines, DMV fees, parking revenue, and other revenue sources, depending upon the various rates of CAV technology adoption as well as the different policy scenarios that are implemented. Another primary product of this research will be a comprehensive analysis of the revenue impacts and opportunities of automated, connected, electric, and shared vehicles accruing at various adoption rates and policy scenarios on the state's transportation system.

The main goals of this research project include an investigation of the impacts of CAV technologies on the current transportation system (specifically intersection capacity at different market penetration levels of the CAVs) and the assessment of the fiscal revenue impacts of CAVs on North Carolina's cities, towns, and households. The objectives of this project are to:

- **Objective 1:** Conduct a comprehensive review of the state-of-the-art and state-of-the-practice on CAV technologies and their impacts on intersection capacity and the associated transportation revenues.
- **Objective 2:** Develop case studies to illustrate these impacts. Considering the impacts of CAVs on the traffic systems, particularly at the intersections, suitable intersections will be identified for the case study.
- **Objective 3:** Create simulation methods to measure intersection capacity at different CAV possible market penetration levels.
- **Objective 4:** Analyze the impacts of the CAV technologies on intersection capacity and provide recommendations for future research directions.

The major goal of this research is to provide an intensive evaluation of the impacts of CAVs on signal intersection systems, as well as an in-depth analysis of intersection capacity adjustment factors and revenue benefits

considering varying MPRs of CAVs. The results of this study could provide a theoretical basis for researchers to investigate the impact of CAVs on currently used signalized intersections. The calibration methods and results of intersection capacity adjustment factors for different CAV penetration rates could provide a guideline for transportation engineers/planners to modify intersection capacity considering the impacts of CAVs. The anticipated research contributions will also benefit transportation practitioners and researchers by enabling them to gain a better understanding of the relationship between intersection capacity and CAVs at different traffic volume levels and market penetrations as well as how the CAVs may affect the transportation revenue generation in the State of North Carolina under different scenarios. The project will also help the NCDOT to design an urban transportation system that can anticipate the impacts of CAVs at different market penetration levels to improve the mobility of people and goods, while providing appropriate levels of revenue to support the improved transportation services. Along that line, the expected contributions of this research are as follows:

- 1. A review of CAV technologies and intersection capacity analysis considering different levels of CAV market penetration.
- 2. Identification of potential intersection scenarios and collection of the characteristics of each transportation revenue impact scenario, including an assessment and feasibility of new, innovative, and sustainable transportation funding methods.
- 3. Guidelines on intersection capacity adjustments at different CAV market penetration levels.
- 4. An evaluation of the fiscal impacts of CAV adoption, including policy options to enable North Carolina to reap the full benefits of CAV adoption.

2.2 Task 1: Literature Review

Under Task 1, we conducted a comprehensive review of the current state-of-the-art and state-of-the-practice on studies related to connected vehicles, autonomous vehicles, and connected and autonomous vehicles. Deployment and market penetration rate prediction, traffic flow control strategy for CAVs, intersection control strategy for CAVs, intersection capacity analysis methods (empirical-based and simulation-based methods), and intersection modeling scenarios and parameters of CAVs were introduced and reviewed. The details of the conducted literature review are presented in Appendix B, Section B.1. This literature survey was intended to provide a fundamental and solid reference to develop control strategies for CAVs at the intersection and conduct effective simulation strategies and impact analysis for future tasks.

2.3 Task 2: Identify Potential Intersections

Under Task 2, we identified potential isolated intersections and collected the necessary data related to the selected intersections. A hypothetical isolated four-way intersection was set as a basic scenario for the simulation. After that, one isolated intersection and two adjacent intersections in North Carolina were selected as potential case study scenarios. The layout, speed limits, peak-hour traffic volume, and pre-timed signal schemes of the intersection were all introduced. One isolated intersection and two adjacent intersections were selected as they could give representative results of the impact of CAVs on the intersection capacity. Also, two adjacent intersections were located between the downtown of Greensboro and the campus of the NCAT. Investigating these two adjacent intersections could give potential insights into Project 3 (which was conducted for using CAVs to connect NCAT's campus to downtown Greensboro sites). This task can be also considered as a basic preparation for simulating intersection capacity with CAVs in future tasks. All scenarios were tested with different MPRs of CAVs to investigate the potential impacts of CAV technologies on the intersection system. The results of this task are presented in Appendix B, Section B.2.

2.4 Task 3: Design Scenarios for the Conduct of Simulation

Under Task 3, we designed specific scenarios for the conduct of the simulation. Empirical methods for intersection capacity calculation and micro-simulation methods for HDVs and CAVs are both introduced. After that, an initial pre-timed signal scheme is designed for a hypothetical isolated four-way intersection. Also, the intersection capacity is calculated by using the empirical method and will be used to compare with the capacity obtained by using the micro-simulation method. Specific scenarios for this typical intersection are designed considering different traffic demands and MPRs of CAVs. Moreover, two types of real-world intersections in North Carolina, including one isolated intersection and two adjacent intersections, were also tested to investigate the potential impacts of CAV

technologies on the intersection system. The details of achievements under this task are presented in Appendix B, Section B.3. The results under this task were served as basic preparations for simulating intersection capacity with CAVs as explained in the next tasks.

2.5 Task 4: Use Simulations to Examine the Established Modeling Framework

Under Task 4, we utilized an isolated four-way intersection for the capacity analysis simulation. Both the lane-level and intersection-level intersection capacity were investigated. In the lane-level capacity investigation, adjustment factors for the saturation headway and saturation traffic flow rate for each lane group under different MPRs of CAVs were all calculated. In the intersection-level capacity investigation, the maximum throughput of the intersection under different MPRs of CAVs was calculated. Moreover, the fitting curves and fitting functions for the maximum throughput, total waiting time, total CO₂ emission, and total fuel consumption under different MPRs of CAVs were calibrated and investigated. After that, the research team investigated the impacts of CAV penetration rates on the intersection with fixed traffic demands. Three case studies, including one hypothetical isolated intersection, one isolated intersection in Charlotte, and two adjacent intersections in Greensboro, were analyzed. The results of the research under this task are presented in Appendix B, Section B.4

2.6 Task 5: Develop Guideline on the Intersection Capacity Adjustments Considering Different Levels of CAV Market Penetration

Based on the results in Task 4, a comprehensive set of guidelines was developed for calculating the intersection capacity considering different CAV MPRs. The lane-level and intersection-level capacity analysis methodologies were developed to accurately capture the impacts of CAV technologies on the intersection system. Detailed adjustment lookup tables and fitting equations were comprehensively documented during the course of this research. Best practices were also recommended for improving the intersection system by incorporating the use of CAVs in the future. The results are presented in the following sections, which are organized as follows. Section G.2 presents the lane-level and intersection-level methods for the intersection capacity analysis considering mixed traffic environments. Section G.3 summarizes lane-level and intersection-level capacity adjustment factors under different MPRs of CAVs. The lane-level adjustment factors for saturation headways and saturation flow rates are comprehensively documented. Meanwhile, intersection-level adjustment factors for the maximum throughput of the intersection and fitting equations for traffic performance indicators are presented. Finally, This chapter concludes with a summary.

2.6.1 Methods for Intersection Capacity Analysis: The microscopic simulation method is implemented in this research to investigate the impacts of CAVs on the intersection capacity. The main difference between the HDVs and CAVs in the microscopic simulation model is the control mode of longitudinal movement, which mainly controls the acceleration/deceleration, speed, car following gaps, etc. In this research, The IDM is implemented for modeling HDVs. The ACC system is utilized to model CAVs when the CAV is following a HDV. The CACC system is implemented to model CAVs when the CAV is following a CAV. The longitudinal movement controls of the CAVs are expected to significantly improve the efficiency of the roadway/intersection systems.

All simulation scenarios are processed in the SUMO by the TraCI-Python interface. The default lane change model “LC2013” in SUMO is employed for all vehicles. The desired headways for HDVs and CAVs are 1.9 s and 0.6/1.1 s, respectively. Also, other parameters for CACC-controlled CAVs are set according to previous research and projects [187, 208, 255].

The intersection capacity is first analyzed by calculating adjustment factors for saturation headway and saturation traffic flow rate for each lane under different MPRs of CAVs. Then, the maximum throughput and other traffic performance indicators of the whole intersection under different MPRs of CAVs are calibrated and investigated. The details of the lane-group-level and intersection-level capacity analysis methods are summarized as follows:

2.6.1.1 Lane-level Capacity Analysis Method: To determine the capacity of the intersection, the saturation flow of each lane is calculated. The saturation flow s_0 is the maximum traffic that a lane could accommodate per hour. In this research, the simulation method is used to calculate the saturation headway and the adjustment factors with regard to CAV penetration rates. As shown in equation (G.1), the basic saturation headway rate s_0 is obtained by dividing 3600 s with the saturation headway of human driving vehicles h_{HDV} .

$$s_0 = \frac{3600}{h_{HDV}} \quad (2.1)$$

As defined in HCM2016 [117], saturation headway is calculated by the average headway between the fifth and fifteenth passenger cars in a standing queue when the intersection signal changes from red to green. The first four headways are not included due to the start-up loss time. In the simulation, the headway is calculated by the time gap when two successive vehicles (front bumper) are passing over the stop line. Considering the impacts of CAV penetration rates, the h_{HDV} and headways with the mixed traffic (h_{CAV}) could be obtained from the simulations. Then, the headway adjustment factor f_h could be obtained by the equation (G.2). The adjusted saturation flow rate s^* could be adjusted by the headway adjustment factor f_h according to equation (G.3) or the saturation flow rate (SFR) adjustment factor f_s according to equation (G.4).

$$f_h = \frac{h_{CAV}}{h_{HDV}} \quad (2.2)$$

$$S^* = \frac{3600}{f_h \times h_{HDV}} \quad (2.3)$$

$$S^* = f_s \times s_0 = f_s \frac{3600}{h_{HDV}} \quad (2.4)$$

With the headway adjustment factor f_h or the saturation flow rate adjustment factor f_s , the adjusted saturation flow rate for each lane group under different MPRs of CAVs could be calculated. The total capacity of the intersection is computed by the product of the adjusted saturation flow rate and effective green time per cycle ratio. Then the signal intersection capacity is expressed as an hourly rate (or 15 minutes of the peak hour), with the unit of vehicles per hour. The capacity of the signal intersection is the sum of the lane group capacity,

$$\text{Capacity} = \sum_i s_i^* \frac{g_i}{C} \quad (2.5)$$

where s_i^* indicates the saturation flow rate of the critical lane group i . g_i/c is the effective green time per cycle ratio for lane group i .

With the estimated adjustment factors for the saturation headway f_h or the saturation flow rate f_s , the Quick-Estimation Method (QEM), which is introduced in the Highway Capacity Manual [117], is used to calculate the whole intersection capacity. The QEM determines the critical movements based on the signal phases and calculates the critical phase volumes. Then the intersection capacity is calculated based on the maximum traffic volume that the intersection could accommodate in an hour. The main steps of QEM are listed as follows:

Step 1: Identify intersection traffic movements, the number of lanes, and calculate hourly traffic volumes per lane. Usually, the hourly traffic volumes are modified to represent the peak 15-minute period.

Step 2: Design a signal phasing plan and determine the traffic movements in each phase. Each phase usually accommodates two non-conflicting movements. The treatment (protected, permitted, etc.) of each left-turn movement is determined mainly based on the left-turn volume and the opposing through traffic volume.

Step 3: Determine the critical volume per lane group that must be accommodated for each phase. The lane group is divided by the traffic movements in each phase. For example, the exclusive left-turn lane with a protected left-turn phase is usually designated as a specific lane group. The critical movement volume determines the amount of green time that should be assigned to the phase on one signal cycle.

Step 4: Sum the critical phase volumes per phase to determine the overall critical volume that the intersection needs to accommodate.

Step 5: Calculate the overall intersection capacity by determining the maximum critical volume that the intersection can accommodate per cycle. The maximum critical volume is determined by the adjusted saturated traffic flow. For signal-controlled intersections, the HCM QEM recommended 1,710 vph. as a base value for the saturation flow rate with only human-driven vehicles for most purposes. For scenarios with different MPRs of CAVs, the basic s_0 is modified by the adjustment factors of the saturation flow rate.

2.6.1.2 Intersection-level Capacity Analysis Method: In microscopic simulation scenarios, saturation traffic throughput (or maximum throughput) is utilized to estimate the capacity of the intersection. The HCM defines capacity as the maximum number of vehicles that can pass through the intersection under certain traffic, roadway, and signalization conditions. The traffic generation in the simulation obeys the uniform distribution to maintain the peak-hour traffic demands all the time. Each simulation maintains 3600 s with a 0.1 s time step. Meanwhile, a ten-minutes (600 s) warm-up period is added at the beginning of each simulation. This warm-up period aims to eliminate the impacts of insufficiency of traffic generation at the first ten minutes of the simulation.

Table 1. Adjustment factors for saturation headway and saturation flow rate for each lane group under different MPRs of CAVs

CAV rate	Saturation headway adjustment factors			Saturation flow rate adjustment factors		
	Exclusive through	Exclusive left	Shared right	Exclusive through	Exclusive left	Shared right
0.1	0.984	0.98	0.967	1.016	1.02	1.034
0.2	0.958	0.959	0.977	1.044	1.043	1.024
0.3	0.884	0.869	0.938	1.131	1.151	1.066
0.4	0.823	0.852	0.883	1.215	1.174	1.133
0.5	0.821	0.847	0.835	1.218	1.181	1.198
0.6	0.74	0.748	0.815	1.351	1.337	1.227
0.7	0.645	0.698	0.743	1.55	1.433	1.346
0.8	0.632	0.638	0.716	1.582	1.567	1.397
0.9	0.505	0.548	0.655	1.98	1.825	1.527
1	0.441	0.511	0.576	2.268	1.957	1.736

For simulation scenarios with different MPRs of CAVs (increase from 0% to 100% by 10% per step), the maximum throughput is obtained by increasing the traffic demands of the intersection. The maximum throughput value is determined if the throughput reaches a stable value with the increase of traffic demand in the following five simulations. Then, the traffic performances (including maximum throughput, total waiting time, total CO2 emission, and total fuel consumption) for the simulation with the maximum throughput are also documented to investigate the impacts of CAV penetration rates on the intersection.

2.6.2 Adjustment Lookup Tables: In this section, the adjustment factors for the lane-level and intersection-level capacity are all summarized and documented. In the lane-level capacity investigation, adjustment factors for saturation headway and saturation traffic flow rate for each lane group under different MPRs of CAVs are summarized. In the intersection-level capacity investigation, the maximum throughputs of the intersection under different MPRs of CAVs are all documented. Also, the fitting functions for the maximum throughput, total waiting time, total CO2 emission, and total fuel consumption under different MPRs of CAVs are calibrated.

2.6.2.1 Lane-level Adjustment Factors: With the increase of the traffic demands for each lane group, the intersection throughput reaches a maximum value which represents the saturated traffic demands. In this study, each approach of the intersection includes one exclusive through traffic lane, one exclusive left-turn traffic lane, and one shared right and through traffic lane. Table 1 summarizes the adjustment factors for saturation headway and saturation flow rate for each lane under different MPRs of CAVs. The change rates are compared to the base scenario with only human-driven vehicles. Under 100% MPR of CAVs, the saturation headways of through-only, left-only, and shared right and through traffic lanes are about 0.441, 0.511, and 0.576 with respect to the basic headway with only human-driven vehicles. Meanwhile, with 100% MPRs of CAVs, the maximum saturation flow rates for the through, left-only, and shared-right lanes could increase by 126.8%, 95.7%, and 73.6%, respectively.

2.6.2.2 Intersection-level adjustment factors: For the intersection-level simulation, the maximum throughput of the isolated intersection is obtained with the increase in traffic demands. The capacity (i.e., maximum throughput) of the isolated intersection is obtained in the simulation under different MPRs of CAVs conditions. The traffic performances are also investigated under maximum throughput scenarios. Table 2 summarizes the maximum throughput and other traffic performance indicators of the intersection under different MPRs of CAVs. The change rates of the maximum throughput (i.e., adjustment factors of the maximum throughput) compared to the 100% HDV scenario are listed in the last column. The maximum throughput increases steadily under 60% MPRs of CAVs and increases rapidly after 70% MPRs of CAVs. With the increase in the traffic throughput, the total CO2 emission, total fuel consumption, and total waiting time also increase significantly after 70% MPRs of CAVs.

With the results in Table 2, the fitting functions of the maximum throughput (veh/hour), total CO2 emission (kg), total fuel consumption (L), and total waiting time (10^6 s) of the saturated traffic flow with regard to different MPRs of CAVs are also summarized as follows:

$$MaximumThroughput = 2969MPR^3 - 1010MPR^2 + 1505MPR + 4914 \quad (2.6)$$

$$CO_2 = 9003MPR^3 - 11800MPR^2 + 5023MPR + 2052 \quad (2.7)$$

Table 2. Traffic performance under saturated traffic flow with different MPRs of CAVs

MPR	Traffic demand	Total waiting time (s)	Average waiting time (s)	Total CO2 (kg)	Avg. CO2 (kg)	Total Fuel (L)	Avg. Fuel (L)	Maximum Throughput	Adj. Factor
0	5400	658796.4	122	2180.461	0.404	937.329	0.174	4938	
0.1	5600	697819	124.61	2385.617	0.426	1025.52	0.183	5047	1.022
0.2	5600	695985.4	124.28	2282.991	0.408	981.403	0.175	5155	1.044
0.3	6100	860257.7	141.03	2922.059	0.479	1256.132	0.206	5339	1.081
0.4	6200	848790.4	136.9	2854.666	0.46	1227.158	0.198	5565	1.127
0.5	6500	906076.3	139.4	3001.592	0.462	1290.318	0.199	5844	1.183
0.6	6500	787004.7	121.08	2662.238	0.41	1144.432	0.176	6085	1.232
0.7	6800	734282.3	107.98	2636.286	0.388	1133.273	0.167	6494	1.315
0.8	7400	955250	129.09	3204.906	0.433	1377.712	0.186	6973	1.412
0.9	8000	1008473.3	126.06	3539.99	0.442	1521.757	0.19	7568	1.533
1	8900	1157348.1	130.04	4323.411	0.486	1858.534	0.209	8413	1.704

$$Fuel = 3870MPR^3 - 5074MPR^2 + 2159MPR + 882.1 \quad (2.8)$$

$$WaitingTime = 2.166MPR^3 - 2.96MPR^2 + 1.332MPR + 0.6208 \quad (2.9)$$

2.6.3 Summary

This Section summarizes the methods for lane-level and intersection-level intersection capacity analysis. In the lane level capacity investigation, adjustment factors for saturation headway and saturation traffic flow rate for each lane under different MPRs of CAVs are calculated. In the intersection level capacity investigation, the maximum throughputs of the intersection under different MPRs of CAVs are calculated. The traffic performances of the total waiting time, CO2 emission, and fuel consumption under maximum throughputs are also documented. The detailed adjustment lookup tables and fitting equations are comprehensively documented. Traffic engineers and planners are expected to be able to directly use the proposed simulation methods or the adjustment factors to calculate the intersection capacity under different MPRs of CAVs.

2.7 Task 6: Conduct a Revenue Impact Analysis and Propose New Methods

As North Carolina's vehicle fleet, demographics, and consumer preferences change, NCDOT will struggle to meet its expenditure needs from its existing sources of revenue, and new funding will need to be identified and implemented. Under this task, we conducted a comprehensive analysis of the drivers of CAV technology and the associated estimated impacts on transportation revenue collections. This research evaluated the impacts on current revenue generation sources and identified policy options to mitigate transportation budget impacts, allowing North Carolina to reap the full benefits of CAV adoption. The findings are presented in the following sections.

2.7.1 Introduction

NCDOT's revenue portfolio is heavily reliant on the taxation of motor fuels. Approximately 42 percent of its revenue comes from the state Motor Fuels Tax, while the next largest source at 23 percent, Federal funding, is itself largely derived from Federal fuel taxes [55] (Fig. 1). Furthermore, a majority of the remaining funding relies on the personal ownership and operation of motor vehicles.

As a result, the adoption of connected and autonomous vehicles poses a major threat to the financial sustainability of North Carolina's transportation system. As CAVs are adopted, NCDOT's revenues face strong downward pressures from challenges such as electrification, improving fuel economy, and a shift away from driving and personal vehicle ownership.

2.7.1.1 Current revenue sources

2.7.1.1.1 Motor Fuels Tax

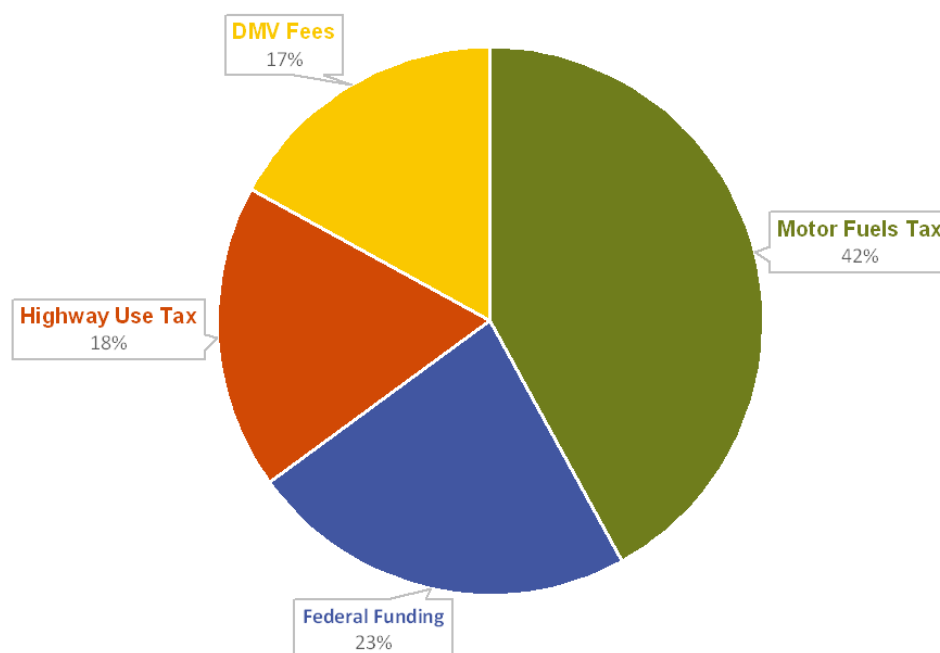
A fuel tax is an excise tax imposed on the sale of fuel. In most countries, a fuel tax is imposed on fuels that are intended for transportation, while fuels used to power agricultural vehicles and/or home heating oil, which is similar to diesel, are usually taxed at a different, lower rate. In the United States, every state imposes its own tax on gasoline in addition to one charged nationwide by the Federal government.

North Carolina charges a tax calculated per US gallon on the purchase of motor fuels. Currently, as of 2023, the rate on both gasoline and diesel is \$0.405 per US gallon, excluding an additional \$0.0025 per gallon inspection tax [222]¹. In state fiscal year (SFY) 2020, North Carolina Motor Fuels Tax revenue totaled \$1.9 billion [56]).

2.7.1.1.2 Federal Funding

23% of NCDOT's total revenue from Federal funding sources [55]. The primary sources of Federal funds are

¹The NCDOR website incorrectly states that the inspection tax is “.0025 cents per gallon” [222]. It is, in fact, “one-fourth of one cent (1/4 of 1¢) per gallon”, which is \$0.0025 or 0.25¢ per gallon



Source: (NC FIRST Commission, 2021, p. 30)

Figure 1. Current NCDOT funding sources

excise taxes charged on gasoline and diesel sales of \$0.183 and \$0.243 per US gallon respectively [83]².

Funds raised from this excise tax are dedicated to the Highway Trust Fund, with \$0.0286 per gallon directed towards the Mass Transit Account and the remainder directed towards the Highway Account [93].

This funding source faces similar pressures as North Carolina's Motor Fuels Tax due to increasing fleetwide fuel economy and changing driving patterns. Furthermore, these rates were last adjusted in 1993, meaning that in real terms they have fallen by over half over the intervening three decades [236]. Fig. 2 shows the loss in real purchasing power due to the Federal gasoline tax remaining at 18.4 cents per gallon since 1993: it has lost over 50 percent of its purchasing power due to inflation. According to estimates from the Bureau of Labor Statistics [236], approximately 38.4 cents in November 2022 is equivalent to 18.4 cents in 1993.

Additional sources of funding for the Highway Trust Fund include taxes on special fuels and truck-specific taxes on tires, sales and heavy vehicle use (charged annually), all of which are solely dedicated to the Highway Account [93]. Federal funding is restricted and cannot be used freely for any project or even any road; in fact, only 28 percent of North Carolina's state highway road miles can possibly receive such funds [55].

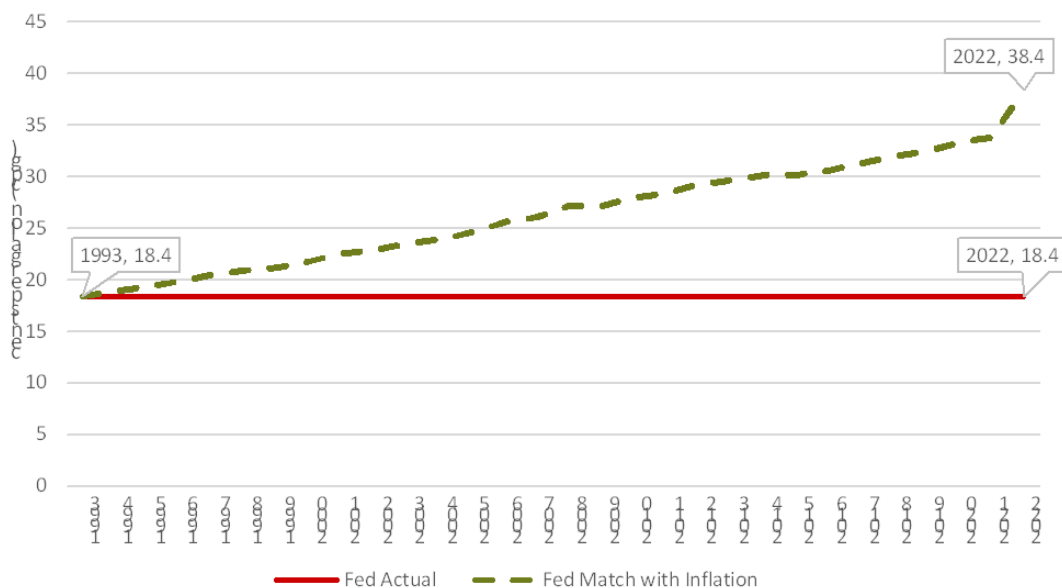
2.7.1.1.3 Highway Use Tax

In 1989, North Carolina switched from a sales tax on vehicle purchases to the Highway Use Tax (HUT). A primary motivation for this change was to direct revenues associated with vehicle purchases into North Carolina's Highway Trust Fund. Today, whenever a vehicle title is transferred in North Carolina, the buyer is charged a one-time, 3 percent tax on the vehicle's purchase price, less any trade-in value if the vehicle was purchased at a dealership [57]. North Carolina's HUT functions similarly to a vehicle sales tax or a standard retail sales and use tax, which are the mechanisms predominantly used in other states to direct sales tax revenue from vehicle sales into a transportation fund. Some states impose vehicle-specific taxes in lieu of a state sales tax, while other states direct a portion of their vehicle sales tax revenue into transportation accounts.

2.7.1.1.3.1 Alternative Highway Use Tax

When a vehicle is leased or rented rather than sold, North Carolina charges an Alternative Highway Use Tax

²An additional \$0.001 is charged per US gallon both to fund underground storage tank cleanup, making the effective rates \$0.184 and \$0.244 per US gallon respectively.



Sources: Authors' illustration; (US Energy Information Administration (EIA), 2022), (US Bureau of Labor Statistics (BLS), 2022)

Figure 2. Federal gasoline tax vs CPI inflation, 1993-present

(AHUT) in lieu of the standard HUT. Long-term leases and rentals are charged a rate of 3%, which is deposited in the Highway Trust Fund. Short-term rentals and leases are charged a rate of 8% and vehicle subscription services are charged an intermediate rate of 5%; however, only a portion of the AHUT charged on these is deposited in the Highway Trust Fund, with the rest remitted the state's General Fund [57].

2.7.1.1.4 DMV Fees

North Carolina uses DMV fees to support a wide variety of uses, most of which are dedicated toward the construction and maintenance of the state's highway network. In 2020, DMV registration fees accounted for approximately 11.4 percent (\$610.3 million) of state transportation revenue, DMV title and other miscellaneous fees accounted for approximately 3.8 percent of revenue (\$201.3 million), and DMV licensing fees accounted for approximately two percent of revenue (\$108.9 million) [223]. Altogether, DMV fees accounted for approximately 17.2 percent of the state's transportation revenue.

2.7.1.1.4.1 Supplemental fee on electric vehicles

North Carolina motorists pay an annual registration fee of \$36 plus an additional annual fee of \$140.25 for plug-in electric vehicles [286]. Proponents support electric vehicle fees to bring equity among drivers by ensuring all drivers pay for using roadways [130]. Across the nation, 28 states have additional registration fees for electric vehicles similar to North Carolina's, ranging from \$50 to \$213 per year [58].

2.7.1.1.5 Other sources

A negligible amount of revenue comes from other sources, such as tolling. Since the opening of the Triangle Expressway, North Carolina's first modern toll road, in 2011, the state's network of tolled roads has grown to 64 miles across three facilities:

- The **Triangle Expressway**, an 18.8-mile toll road in Wake and Durham counties
- The **Monroe Expressway**, an 18-mile toll road in Mecklenburg and Union counties
- The **I-77 Express Lanes**, a 27-mile High-Occupancy Toll (HOT) facility in Mecklenburg and Iredell counties, which was built and is maintained by infrastructure firm Cintra under a public-private partnership agreement

Two further projects are under construction—an extension of the Triangle Expressway and the addition of HOT lanes to Interstate 485 in southern Mecklenburg County—and, as of December 2022, three other projects are under development [224]. Under current law, the NC Turnpike Authority is required to spend the money raised by its toll facilities on the same toll facility, on a contiguous toll facility, on debt service, or on Authority administration [9].

2.7.1.2 Comparison to other states:

North Carolina is more reliant on funding from motor fuel taxes than most other states for maintaining its highway network. This is especially true once Federal funding is removed: according to a Tax Foundation analysis, with Federal funding excluded, 66% of state highway funding in North Carolina in FY2018 came from Motor Fuels Tax, ranking North Carolina 14th among US states. By contrast, the average state sourced only half its highway funding from fuels taxes. A comparison of the relative shares of funding by source for NC vs all states is shown in Table 3.

Table 3. State-sourced highway revenues, FY2018

Revenue source	Share among all states	Share in NC	Rank among states
Motor Fuels Tax	49%	66%	14
License revenue	30%	32%	21
Tolls and charges	21%	2%	39

Overall, the Tax Foundation analysis found that North Carolina state-sourced revenues were slightly less reliant (65 percent) on these user fee sources than the typical (median) state (66 percent)³.

2.7.2 Revenue challenges

2.7.2.1 Changing patterns of car usage:

In the short-term, as technology, demographics and population preferences change, lower overall rates of driving and car ownership are expected [55]. Already, the number of miles traveled per person in North Carolina appears to be leveling off [56]. This could put downward pressure on many of NCDOT's present funding sources. Both lower levels of driving and lower levels of car ownership would pressure the DMV fee and the Highway Use Tax revenues (see the Decreased fee and HUT revenue below), while decreased driving overall would pressure the Motor Fuels Tax and possibly toll revenues.

However, over a longer time horizon, it is possible that vehicle miles traveled may increase if connected and autonomous vehicles (CAVs) become a significant mode of travel for North Carolinians. CAVs may change the value of time for car usage, lowering the opportunity cost of taking a car and making users willing to travel by car more, rather than less.

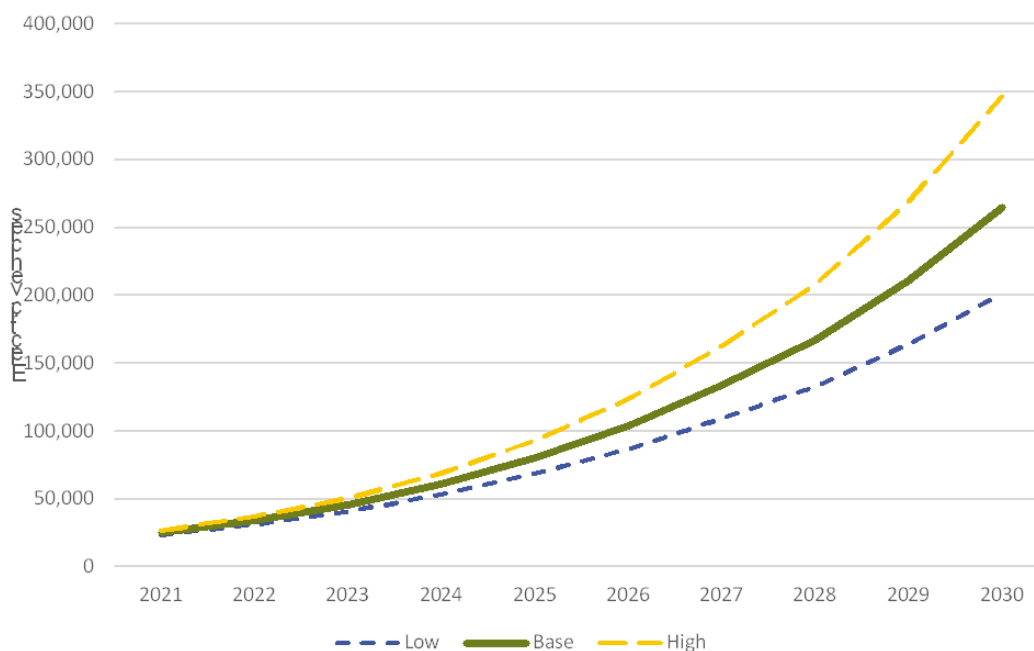
2.7.2.2 Electrification:

Virtually all CAVs are presumed to be electric vehicles (EVs), and EVs necessitate the use of different tools to raise revenue than the fuel taxes charged to conventionally-powered vehicles. While, as of 2022, electric vehicles make up a small share of the cars on North Carolina roads, that's changing fast. By 2030, over 250,000 vehicles on North Carolina's roads are predicted to be EVs (Fig. 3).

At the moment, North Carolina charges an annual supplemental fee of \$140.25 for electric vehicle registrations to compensate for the revenue lost due to their energy source not being subject to the Motor Fuels Tax. Using DMV data, the NC FIRST Commission found that an EV owner in North Carolina paid \$50 less than the owner of a typical vehicle in 2020 [58]. However, this analysis suffered from a core deficiency: the typical vehicle in North Carolina is not an appropriate comparator. While the typical vehicle in North Carolina as of 2020 was 12.7 years old [58] and had a fuel economy of 22.7 miles per US gallon [56], most EVs on the road are late model and either sedans, hatchbacks or smaller SUVs. Similar late model sedans and SUVs powered by gasoline would also generate much less in Motor Fuels Tax revenue than the typical vehicle on North Carolina's road, yet the NC FIRST Commission does not argue that the purchase of a new Toyota Corolla results in "revenue lost" even though this vehicle too would pay less than the state's average vehicle. (The adverse revenue impacts from the increased efficiency of late-model, conventionally-powered vehicles are discussed further in Improving fuel economy below.)

The North Carolina Clean Energy Technology Center performed a different analysis that instead compared North Carolina's EV fleet to conventionally-powered vehicles of similar age and size and estimates that, as of 2019,

³Note that the Highway Use Tax (HUT) is not considered a user fee



Source: Internal NCDOT forecast from NC ZEV Plan

Figure 3. NC electric vehicle adoption forecast

the state lost \$100 in Motor Fuels Tax revenue per electric vehicle. At the time, however, the EV registration fee was \$130 per year, and therefore electric vehicle owners contributed on average \$30 more per vehicle than owners of comparable vehicles. This meant that, in total, electric vehicles resulted in a net surplus to NCDOT of \$360,000. The Center projects that foregone gas tax revenue through 2025 will be between \$103 and \$110 per vehicle [44]. Applying this to the NC ZEV Plan's projections of the size of the state's EV fleet in 2025 results in estimated excess revenue to NCDOT of between \$2.075 million and \$3.475 million⁴.

While electric passenger vehicles currently create a surplus and can be expected to continue to do so in the near future, the adoption of electric heavy vehicles may pose a significant threat: the Clean Energy Technology Center estimated that the lone electric tractor-trailer registered in North Carolina in 2019 may cost the state \$3,800 in lost MFT revenue if it travels a typical number of miles each year [44]. If intercity trucking on limited-access highways proves to be an early application of autonomous technology, then the first CAVs on North Carolina's roads may impose a significant fiscal impact on NCDOT.

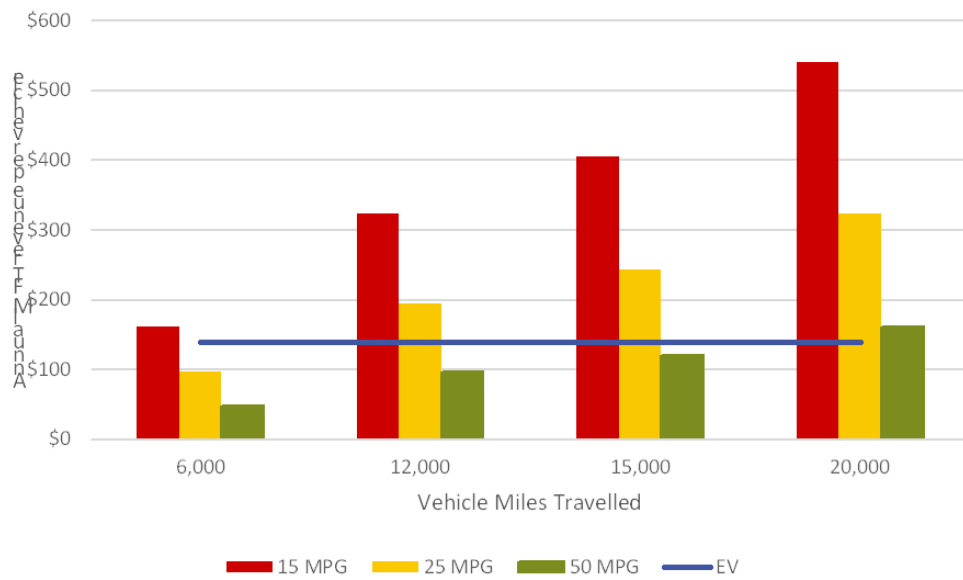
2.7.2.3 Decreased fee and HUT revenue:

CAV adoption will likely result in a relatively larger share of North Carolinians choosing to go without a driving license, as one would presumably not be needed for their autonomous journeys. This would decrease the revenue that NCDOT generates from driver licensure.

Similarly, it is possible that CAV adoption may cause relatively more North Carolinians to forego car ownership altogether, choosing instead to request on-demand rides from corporately-owned autonomous taxis. This relative shrinking of the overall size of the vehicle fleet would reduce the amount of revenue that NCDOT receives from per-vehicle registration and titling fees. A smaller vehicle fleet may also mean a decrease in the amount of Highway Use Tax (HUT) raised; however, the decrease in HUT from fewer overall vehicles may be offset by the likely higher per-vehicle value of CAVs.

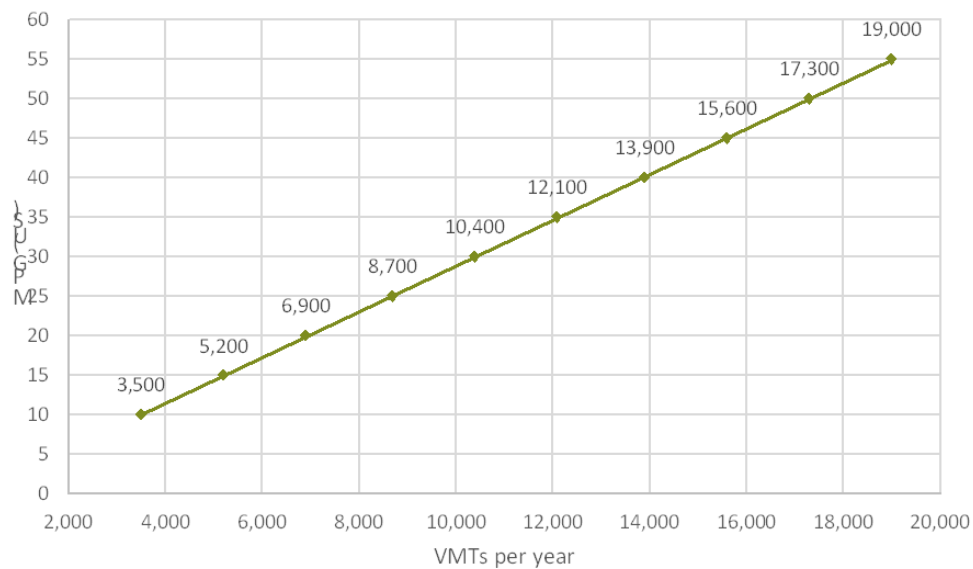
2.7.2.4 Improving fuel economy:

⁴\$2.075 million in surplus EV revenue assumes NC ZEV's "low" scenario of 68,600 EVs in 2025, an EV registration fee of \$140.25 and lost MFT per vehicle of \$110; \$3.475 million in surplus EV revenue assumes NC ZEV's "high" scenario of 93,217 EVs in 2025 and lost MFT per vehicle of \$103.



Source: Authors' calculation based on current Motor Fuels Tax and EV registration fee rates

Figure 4. Annual Motor Fuels Tax revenue by VMT as MPG (US) improves



Source: Authors' calculation based on current Motor Fuels Tax and EV registration fee rates

Figure 5. Breakeven analysis: Current electric vehicle fee vs MFT revenue

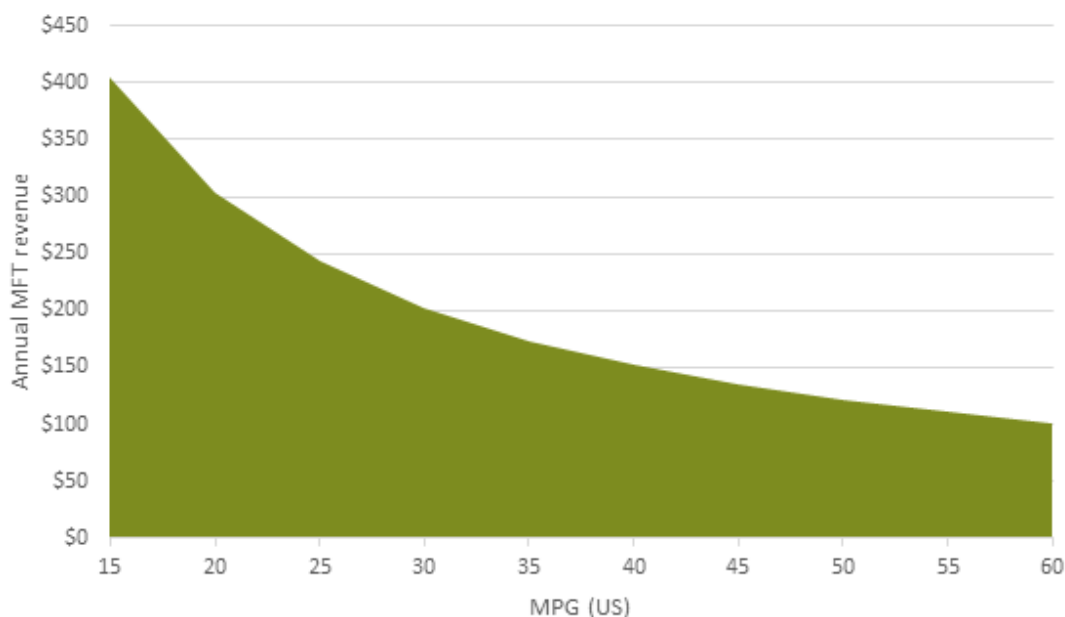


Figure 6. MFT revenue at 15,000 VMTs per year as MPG improves

It is important to note that in the short term, the largest threat to NCDOT's finances comes not from the adoption of CAVs (or other alternative fuel vehicles) but from improving fuel economy among conventional vehicles.

Small nominal changes in fuel economy for the least efficient vehicles have an outsized effect on fuel consumption and, therefore, on NCDOT's revenues. As seen in Figure 6, at the current MFT rate of \$0.405 per US gallon, replacing a vehicle with a fuel efficiency of 15 MPG (US) that travels 15,000 miles in North Carolina each year with one with a fuel efficiency of 20 MPG (US) decreases NCDOT's revenues by over \$100, while replacing a 35 MPG vehicle traveling that same distance with a 40 MPG one would reduce NCDOT's revenue by less than \$25. In summary, a 5 MPG improvement would cause more than four times the MFT revenue loss at 15 MPG compared to at 35 MPG.

This effect is more clearly seen when the fuel economies are stated in gallons per 100 miles, rather than miles per gallon. A vehicle with a fuel economy of 10 mpg consumes 10 gallons per 100 miles while one with 15 mpg consumes 6.6 gallons per 100 miles; a vehicle with a fuel economy of 25 miles per gallon consumes 4 gallons per 100 miles, while one with 50 mpg consumes 2 gallons per 100 miles. Thus, while the nominal change in fuel economy from going from 10 mpg to 15 mpg is much smaller, the absolute change in fuel consumption is much greater.

In 2010, the average vehicle in North Carolina had a fuel economy of around 20.5 mpg. Between 2010 and 2020, the fuel economy of North Carolina's vehicle fleet improved by 2.4 mpg, resulting in a figure that was by the end of that decade almost 23 mpg [56]. For the typical vehicle, this has already resulted in a decreased consumption of almost 64 gallons per year, representing a reduction in Motor Fuels Tax revenue of about \$23 per vehicle (as well as a reduction in Federal gas tax revenue of about \$9) each year by the end of the decade.

These improvements are only expected to continue: by 2026, new cars are predicted to have an average fuel economy of 47.7 mpg and new light trucks 34.1 mpg [55]⁵. The revenue challenge this poses to NCDOT greatly exceeds that of CAVs in any reasonably forecastable time horizon.

2.7.3 Revenue options

A variety of options are available to address any potential revenue shortfall due to the transition to CAVs, including reforms to existing funding sources as well as entirely new mechanisms. All, however, have trade-offs that need to be fully explored and considered before implementing changes to the current funding paradigm.

2.7.3.1 Implementation of a Road User Charge:

A road user charge (RUC), also frequently referred to as a vehicle miles traveled (VMT) tax, VMT fee,

⁵The fuel economy of the state's vehicle fleet as a whole, of course, lags that of its newest vehicles.

or mileage-based user fee (MUBF), is a policy of charging motorists based on how many miles they have traveled. Instead of using a tax on fuel consumption as a way of financing transportation infrastructure, motorists are charged based on their road usage measured by distance travelled. These charges can be a flat fee (e.g., a fixed number of cents per mile, regardless of where or when the travel occurs), a variable fee based on considerations such as time of travel, congestion levels on a facility, type of road, type, and weight of the vehicle, vehicle emission levels, and the owner's ability to pay, or a combination of flat and variable fees.

In the US, 24 states are actively monitoring road user charge policies and programs, eight have either completed or are in the process of planning an RUC pilot program, and two states have active road user charge programs [237].

2.7.3.1.1 Advantages

Vehicle miles traveled, especially once adjusted for the weight class, is a fiscally-efficient proxy for the costs incurred by NCDOT. Therefore, if structured appropriately, the amount that each vehicle operator pays under an RUC system could closely approximate the share of NCDOT's costs attributable to that vehicle. These and other characteristics make RUCs highly favored among economists.

For CAVs that are part of corporately owned managed fleets, the necessary data to implement such a charge will likely already be collected by the vehicle owner.

2.7.3.1.2 Challenges

The implementation of such a system would be difficult, especially if imposed on non-CAVs or on any CAVs owned by individuals. For these users, location-based systems of administration may raise privacy concerns, while odometer-based systems may be subject to fraud or receive objections from those vehicle owners with significant travel out-of-state or on other non-NCDOT roads. Rural vehicle owners may be especially likely to object, even though most analyses show they would benefit relative to other road users, as rural drivers tend to make fewer, but longer, trips in less efficient vehicles.

Unlike most other options, there is currently no infrastructure in place for the collection of an RUC.

In polling asking North Carolinians about their preferred mechanism for funding the state's transportation infrastructure, an RUC was not among the most preferred options; it was, however, most popular among focus group participants [201]. This gap between the views of poll respondents and focus group participants suggests that an RUC's unpopularity in polling may be due to a lack of familiarity among the public.

2.7.3.2 Motor Fuels Tax reform:

Under current state law, the Motor Fuels Tax is adjusted annually based on changes in population and in the Consumer Price Index for energy [55]. However, changes in the price of energy are not particularly reflective of changes in NCDOT's costs.

The Motor Fuels Tax could be reformed in a variety of ways, including:

- Annual adjustment to more closely match NCDOT expenditures
- Annual adjustment based on an index of construction costs

2.7.3.2.1 Advantages

The Motor Fuels Tax continues to have significant advantages. Administration is exceedingly simple and efficient, with the collection infrastructure already in place, and evasion is difficult.

The Motor Fuels Tax also furthers the state's environmental goals, as fuel consumption is a reasonable proxy for pollution externalities. The state currently has a policy of reducing carbon emissions to 40% below 2005 levels and increasing the number of zero-emission vehicles to 80,000 by 2025 [234].

2.7.3.2.2 Challenges

If MFT continues to be the largest funding source for NCDOT, then, over time, as the vehicle fleet moves to CAVs and other vehicles powered by alternative sources of energy, more and more of the burden for building and maintaining North Carolina's road network will fall upon fewer and fewer motorists—i.e., those who still own conventional gasoline- or diesel-powered vehicles.

Though North Carolina's motor fuel tax (\$0.405 per gallon including \$0.0025 inspection tax) is only marginally higher than the national average of \$0.3869, this average is brought up by much higher taxes in states like California, Illinois, and Pennsylvania; the median state, Utah, charges \$0.3191 per gallon [131]. More pertinently, North Carolina's fuel tax is higher than that of its neighboring states—and, in the cases of Tennessee and South Carolina, much higher [116]. Avoidance of the Motor Fuels Tax is possible and is especially easy for those who live

close to North Carolina's borders with its adjacent states, including many residents of the state's largest metro area, the Charlotte-Concord-Gastonia MSA. Though the current extent of such leakage is not known, the incentive to cross state borders to avoid North Carolina's Motor Fuels Tax increases as the difference between North Carolina's rate and those in neighboring states grows.

Fuel consumption is an inferior proxy for a vehicle's share of capital and maintenance expenditures compared to miles traveled, though it is a superior proxy to the Highway Use Tax and to flat fee sources of revenue.

2.7.3.3 Hypothecated sales tax:

Retail sales taxes apply to the final sale or lease of most goods and some services. 45 states and the District of Columbia collect a general statewide sales tax. States may also levy selective sales taxes that are used to finance their transportation systems, which may include granting local governments the authority to impose additional tax increments for transportation purposes. From 2013 to 2020, a total of 26 bills related to the use of sales taxes for transportation system funding were enacted across the United States [225]. All states using the state sales tax method also employ other methods to fund transportation.

North Carolina has a state-levied sales tax of 4.75 percent, effective July 1, 2011, with most counties adding a two percent tax, for a total tax of 6.75 percent in 72 of the 100 counties. Among other allowed purposes, the state does allow counties to impose a 0.5 percent sales tax to support public transit, subject to voter approval by popular vote [358]. Durham, Mecklenburg, and Wake counties levy such an additional 0.5 percent tax, which is directed toward funding their respective transit systems. The maximum combined state and county sales tax allowed in North Carolina is 7.5 percent. Two counties (Durham and Orange) have met this cap, while the state's two most populous counties (Wake and Mecklenburg) are 0.25 percentage points below this cap (i.e., the combined rate in these counties is 7.25 percent).

This reform has now been partially adopted. In 2022, North Carolina's general assembly transferred an additional \$193 million in sales-tax revenues to the state highway fund [164]. By 2025, it is anticipated that revenue transfers will triple to \$600 million a year and continue at about six percent of annual sales tax in future years [164].

2.7.3.3.1 Advantages

A small nominal change in the sales tax rate can create large revenues relative to NCDOT's budget, and the additional costs of implementation and administration are negligible.

Raising the state sales tax was generally the most popular option among poll respondents in North Carolina asked about their preferences for funding North Carolina's roads, though no option was ever the first preference of an outright majority [201].

2.7.3.3.2 Challenges

A significant pitfall of sales tax diversion stems from its violation of the "user pays" principle. As highway users pay less in motor fuel taxes at the pump and more through general sales taxes, the link between the use of the state's highway network and funding for the state's highway network weakens, and motorists may lose the ability to relate their actions to the taxes they pay allocated to transportation. As a result, drivers may drive more and increase roadway congestion. Additionally, North Carolina's sales tax is regressive by nature, which means those who earn less would be required to pay a larger share of their income to support transportation. Regressivity can be remediated through other policy measures. With North Carolina's greater focus and awareness of equity issues, measures to alleviate regressive tax impacts should be evaluated.

2.7.3.4 Highway Use Tax reform:

North Carolina does not charge sales tax on purchases of motor vehicles. Rather, it charges a Highway Use Tax (HUT) of 3 percent of the purchase price, net of any trade-in value. This rate is significantly lower than the base 4.75 state sales tax on most purchases—and much lower than the top rate in some counties of 7.5 percent. The rate charged in North Carolina is also significantly lower than those charged in most of its neighbors, which can be twice as high or more [55].

The Highway Use Tax currently makes up 17 percent of NCDOT revenues [55].

2.7.3.4.1 Advantages:

Administration of the Highway Use Tax is relatively simple, with the necessary mechanisms already in place.

The current lower rate of HUT assessed on vehicle purchases relative to the sales tax charged on other forms of goods consumption acts as a *de facto* subsidy on automobile purchases. Raising the rate to more closely match that charged on most other purchases would help to eliminate this implicit subsidy.

HUT is currently calculated net of trade-in value when conducted at a dealership; eliminating this carve-out

would end an implicit subsidy to dealerships.

2.7.3.4.2 Challenges:

This would face organized opposition from, among others, motor vehicle dealers.

The price of a vehicle is not closely related to NCDOT's costs associated with that vehicle, and, as HUT does not disincentivize marginal driving, it results in the least frequent drivers subsidizing those who drive the most.

If CAVs lead to a decrease in vehicle ownership as users instead request "on-demand" rides, the relative number of vehicles on the road would decrease as well, shrinking the HUT base, though this could be offset by the likely higher value of CAVs relative to contemporary vehicles.

2.7.3.5 Increased fee revenue:

The Division of Motor Vehicles collects a variety of fees, most notably for title, registration, and licensure. There is also a supplemental registration fee of \$140.25 for electric vehicles, intended to offset lost Motor Fuels Tax receipts. DMV fees currently make up 18 percent of NCDOT revenues. In 2015, these fees were adjusted upwards by 30 percent, and, starting July 1, 2020, are subject to an inflation-based adjustment every four years [55].

NCDOT could shift towards a greater share of the revenue from all drivers and vehicles being fee-derived, or it could continue to increase the amount charged to electric vehicles in particular.

2.7.3.5.1 Advantages:

The administration is very efficient, and evasion of these fees is difficult.

2.7.3.5.2 Challenges:

Presumably, CAVs would obviate their users' need for a driving license, and the number of licensed drivers would decrease over time, reducing licensure fees as a source of revenue. Similarly, if CAVs result in their users foregoing car ownership, the relative size of the vehicle fleet may decrease as well, reducing fee revenue from titling and registration. Moreover, as these fees are charged per vehicle, this decrease would not be offset by the higher value of CAVs (see Highway Use Tax reform above). These challenges could be offset, however, through increased rates.

A flat-rate fee on a vehicle or driver is a very poor proxy of the capital and maintenance expenditures associated with that vehicle or driver. Those who drive the least would subsidize those who drive the most, and drivers would be incentivized to drive more than they would otherwise were they bearing the actual marginal cost of their driving.

As discussed (see Electrification above), the existing additional fee charged for EVs likely exceeds the Motor Fuels Tax that would be collected on similar conventionally powered vehicles, and an increase may act as a further effective subsidy to gasoline vehicles, which may be contrary to non-revenue policy goals, such as the state's current goal of reducing carbon emissions to 40% below 2005 levels and increasing the number of zero-emission vehicles to 80,000 by 2025 [234].

2.7.3.5.3 Revenue projection:

The amount of revenue raised from the EV supplemental registration fee depends on the rate selected. Fig. 7 compares the projected revenue raised from the current fee compared to that from raising the fee by 50% and by 100%, based on NCDOT's current forecast of electric vehicle adoption. As shown in Fig. 8, however, any of these rates are expected to exceed lost MFT in the year 2025.

2.7.3.6 Taxes on alternative fuels

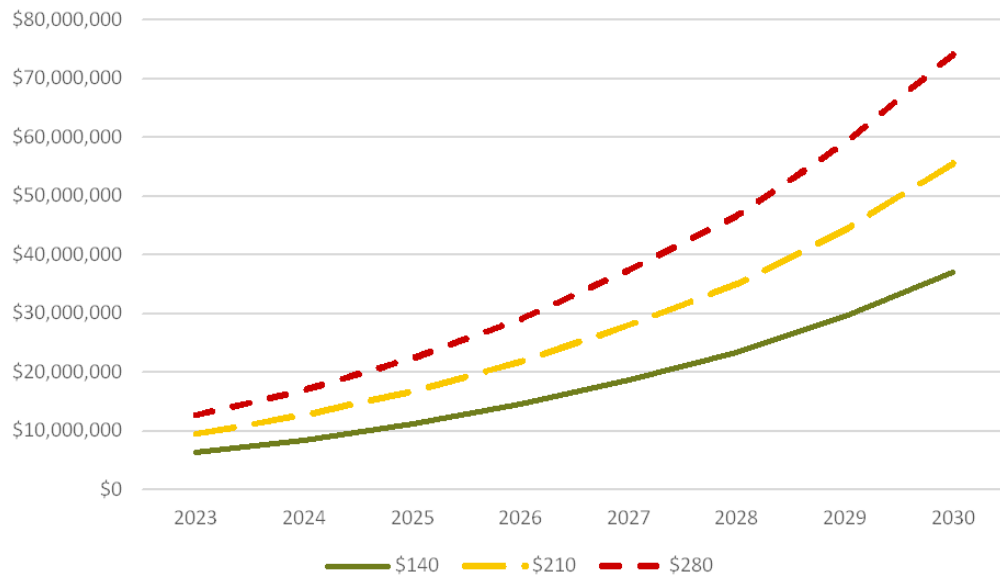
Some states have imposed taxes on non-gasoline/diesel fuels used for vehicle operation, including not only other hydrocarbons like propane or natural gas but even electricity. North Carolina already taxes ethanol propane, compressed natural gas, and liquefied natural gas on a gasoline-gallon or diesel-gallon equivalent basis [44].

2.7.3.6.1 Advantages:

Unlike flat rate fees, and like the Motor Fuels Tax or a Mileage-Based User Fee, taxes based on fuel consumption preserve the disincentive on marginal driving and lessen the subsidy from those who drive the least to those who drive the most.

2.7.3.6.2 Challenges:

Collection and compliance enforcement for a tax on electricity used specifically by CAVs and electric vehicles may be difficult. No existing method exists for the collection of such a tax, and segregating electricity used for vehicles from that used for other purposes may be challenging to do in a reliable way, especially at the household level. For example, Pennsylvania requires drivers to record usage and to calculate, report, and remit the tax owed [58], while a proposed tax in Iowa would only be charged at locations "other than a residence" [11]. It is possible, though,



Source: Authors' illustration

Figure 7. Projected EV supplemental registration fee revenue at various rates



Sources: Authors' illustration; (Brutz & Carr, 2019)

Figure 8. EV supplemental fee vs lost MFT, 2025

that corporate fleet owners of CAVs will be more capable and willing to comply with a tax that required reporting consumption of electricity for the purpose of vehicle charging than would be individual vehicle owners.

The correct basis for rate determination may also be difficult. Pennsylvania’s tax is based on the energy content of the alternative fuel and designed to be equivalent to on this basis to the state’s gasoline tax [58]. In 2023, Iowa will begin charging a rate that is 50 percent higher per kilowatt-hour than that charged in Pennsylvania [58]—despite its gasoline tax being roughly half that of Pennsylvania’s [131])—and which will be collected in addition to a supplemental registration fee of \$130 [11].

2.7.3.7 Increased toll revenue

As of 2021, there are three tolled facilities in North Carolina, with four more projects underway [55] [224]. Currently, state law requires that tolls must be used on the same project from which they were collected or on a contiguous facility [9]. Toll revenues could be increased in a variety of ways:

- State law could be changed to allow toll revenues to be used for other NCDOT purposes.
- Additional tolled facilities could be constructed.
- Tolling could be added to existing facilities.

2.7.3.7.1 Advantages:

Similar to an RUC, a well-calibrated toll can be an extremely accurate proxy for a vehicle’s capital and maintenance burden on the tolled roadway itself. Tolls, therefore, align with the “user pays” principle on highways on which they are charged.

2.7.3.7.2 Challenges:

Using toll revenues for NCDOT purposes other than the facility on which the toll was collected violates the “user pays” principle.

The construction of new tolling facilities and the introduction of tolling to existing facilities are time-consuming and require significant upfront capital investment. It is unlikely that such investments will ever be made in North Carolina on roads that are not limited-access highways.

The addition of tolling to existing facilities would likely encounter significant public resistance. Furthermore, section 129 severely curtails the state’s ability to toll existing Interstate and other Federal-aid highways, with only narrow exception [92].

2.7.3.8 State appropriations:

Currently, NCDOT relies on hypothecated (or dedicated) revenue streams to fund its operations. This is quite unlike most other state agencies, few of which are almost entirely dependent on dedicated revenue sources and most of which instead rely primarily on appropriations from the North Carolina General Assembly, which appropriates funds by weighing agency needs against available revenues. NCDOT could transition to being funded more like other state government agencies.

2.7.3.8.1 Advantages:

In general, expenditures tend to rise to fill the available funds, both for individuals and for organizations. If department funds were appropriated by the General Assembly instead of set by hypothecation, there would be a greater ability to match available funds with NCDOT’s actual expenditure needs. Correspondingly, there would also be greater public oversight and scrutiny of NCDOT spending.

2.7.3.8.2 Challenges:

Relying on state appropriations does not solve a potential revenue shortfall at NCDOT. Rather, it simply shifts the problem elsewhere. Funding for North Carolina’s transportation network will still need to be found, just from other potential revenue sources, such as income, sales, corporate income, and franchise taxes, or from reduced expenditures elsewhere. Furthermore, the “user pays” principle would be significantly weakened.

Finally, relying on appropriations may reduce the stability of NCDOT funding, hampering future planning.

2.7.3.9 Introduce a tax or fee on for-hire vehicle trips:

A tax or fee could be charged on for-hire vehicle (FHV) journeys, either only those taken in CAVs, only those in EVs, or those in all FHVs.

Currently, in North Carolina, trips in “ridesharing” vehicles are entirely untaxed—including being free of sales tax—and local taxes and fees on such trips are also prohibited. Only 11 other states take North Carolina’s tax-lite approach to such journeys [162].

2.7.3.9.1 Advantages:

FHV journeys are expected to be a common application of CAVs. A tax or fee could be administratively simple to operate. A per-trip fee would be transparent and easy to calculate, increasing its salience.

2.7.3.9.2 Challenges: A fee charged either per trip or as a percentage of the fare charged would be a poor proxy for the costs that a trip imposes on NCDOT. A fee charged to users per VMT would be superior, though it may not be transparent to users and would be a worse proxy for the costs imposed than an RUC charged on the operator on all vehicle miles traveled (see Implementation of a Road User Charge above). (An RUC charged to operators only on VMTs when a vehicle is occupied would have equal incidence to a per VMT fee charged to a passenger on a private journey, i.e., the economic and tax consequences of these would be equivalent for all parties, despite the tax supposedly being owed by a different entity.)

The General Assembly has been reluctant to impose taxes specifically on “ridesharing” trips.

2.7.3.10 Transfer of facilities:

North Carolina has an unusually large state highway system. There are no county roads in North Carolina: a public road is maintained either by the local municipality or by the state itself. Many seemingly local roads in North Carolina are maintained by NCDOT and not by the municipality in which they are located. As a result, North Carolina’s state-maintained highway system comprises nearly 80,000 miles, second only to that of Texas. North Carolina could choose to adopt a system more similar to that of most other states, where municipalities and/or counties take on a greater share of the responsibility for maintaining local roads.

2.7.3.10.1 Advantages:

NCDOT would face lower maintenance costs due to the transfer of facilities to other entities.

2.7.3.10.2 Disadvantages:

This proposal would almost certainly face unified opposition from North Carolina’s 552 municipalities and 100 counties. Currently, there are no county roads in North Carolina. Counties do not now have the physical or organizational infrastructure to accept this responsibility.

Moving responsibility for a greater share of North Carolina’s roadways to lower tiers of government does not solve a potential revenue shortfall. Rather, it simply shifts the problem from NCDOT to local governments. Funding for North Carolina’s transportation network will still need to be found, just from the other potential revenue sources that are available to local governments, such as local property and sales taxes.

2.7.3.11 Other mechanisms

2.7.3.11.1 Hypothecated income tax:

A diversion of a portion of North Carolina’s state personal income tax could, similar to that of sales tax, create large revenues relative to NCDOT’s budget with negligible implementation and administration costs. There would, however, be, significant challenges to taking such a measure. The state constitution caps the personal income tax rate at 7%, but North Carolina’s rate, which as of January 2023 is a flat rate of 4.99 percent, has been successively cut over the last decade and is scheduled to continue to decrease to 3.99 percent by 2027 [193]. A dedication of a portion of income tax for the state’s transportation needs would be competing for increasingly constrained funds with the many other state policy priorities that are funded by income tax. Moreover, diverting income tax would suffer from the same violation of the “user pays” principle as the dedication of sales tax (see Hypothecated sales tax, above).

2.7.3.12 New taxes or fees on non-motorists:

Motorists are not the only users of NCDOT highways. Bicyclists, pedestrians, and transit riders benefit from these facilities, as well. Additional fees, such as an additional sales tax or registration fee for bicycles or a fee for transit trips, have been proposed. However, expenditures imposed by these groups are minimal, implementation and administrative costs would be high, and there are significant environmental and economic equity concerns when increasing costs on these road users. Most pedestrians, cyclists, and transit users are also motorists, and all pay state sales tax on their retail purchases. Moreover, transit vehicles do currently incur at least some of the taxes and fees that owners of other vehicles must pay.

2.7.3.13 Tire tax:

Due to the additional infrastructure burden imposed by the heaviest vehicles, purchases of tires with a maximum rated load greater than 3,500 lbs. are subject to an additional tax at the Federal level of \$0.0945 for every 10 lbs. of rated load above 3,500 lbs.

North Carolina could consider paralleling this measure with a state tax. This would not raise a great deal

of revenue on its own nor would it be effective in capturing costs from out-of-state vehicles traveling on North Carolina roads. Furthermore, unlike its Federal counterpart, a state tire tax would be more prone to avoidance from the shifting of registrations of commercial vehicles outside the state and/or to evasion from out-of-state tire sales for North Carolina-registered vehicles.

A tire tax could also be implemented for all tires sold in the state. Such a tax would face similar challenges, though at a greater scale: a tax low enough to minimize avoidance would raise little revenue, while a high tax rate would result in widespread avoidance.

2.7.4 Conclusion:

As North Carolina's vehicle fleet, demographics, and consumer preferences change, NCDOT will struggle to meet its expenditure needs from its existing sources of revenue, and new funding will need to be identified and implemented. Multiple options for this exist, including reforms to existing sources as well as the creation of new revenue streams. Ultimately, the state will likely need to adopt a blend of multiple approaches.

Chapter 3 : Research Findings under Thrust 2 (Assessing North Carolina Readiness for CAVs in Traditional and Emerging Infrastructure Needs)

3.1 Background

The deployment of connected and autonomous vehicles (CAVs) has been widely touted as a potential solution to many of the challenges facing the transportation industry, including traffic congestion, air pollution, and road safety. However, the successful implementation of CAVs requires a robust and reliable infrastructure to support their operation. This project highlights the need to investigate the transportation infrastructure readiness prior to the deployment of CAVs, as it plays a crucial role in ensuring the successful implementation of this transformative technology.

It is expected that the implementation of CAVs in North Carolina's highway networks can lead to improved safety and enhanced operational efficiency. The Connected and Autonomous technologies can be thought of as two separately developed concepts, both of which will need additional safeguards before autonomous systems supplement or replace on-vehicle sensors with Connected Vehicle (CV) messages. Currently, CV Systems are developed and tested in close coordination with public agencies as USDOT has long supported CV technology and standards development and now has multiple CV field test deployments across the US. Public agencies remain a critical partner in CV deployment as any Vehicle-to-Infrastructure (V2I) systems must coordinate with the infrastructure owners. This contrasts with current developments of Autonomous Vehicles (AVs), where private industry has led development and IP concerns often restrict the flow of information on their deployment to the public.

NCDOT has a vested interest in understanding how Connected and Autonomous technologies develop, as changes to future requirements such as the MUTCD or other design standards may be costly to implement without proper planning for and integration into the department's day-to-day business practices. In 2016, NCDOT released the report "NC Readiness for Connected and Autonomous Vehicles (CAV)," which identified many needs in the state, including a focus area on transportation infrastructure. This report also led to the creation of a committee on Highly Automated Vehicles which includes a subcommittee on Infrastructure.

As the technologies needed to safely operate a single Highly Automated Vehicle mature, the real challenge comes from reliable, safe, real-time operation of CAVs in massive scale. Also, mission-critical services drive the need for building CAV systems to ensure ultra-low end-to-end delay down to the 1 ms range. However, based on existing communication protocol/signaling-based vehicular networking, the traditional infrastructure can only support latency in the range of 100 ms. These conventional infrastructure solutions inevitably incur physical feedback transmissions, cumbersome and reactive protocol stacks, undesirable long backhaul delay, and failures of handling high vehicle mobility in real-time. There is also significant risk associated with cyberattacks on the CAV systems, where human lives are the cost of system failure or intrusion.

This project will therefore explore needed changes to the existing infrastructure along with emerging technological support for CAV integration into North Carolina's transportation system. The primary objectives of this research project are:

- **Objective 1:** Document NCDOT Infrastructure Programs Impacted by CAV Needs.
- **Objective 2:** Develop and Test a 5G Architecture for Secure V2I Applications.
- **Objective 3:** Recommend Program Enhancements to Advance NC CAV Infrastructure Readiness.

The first objective centers on a review of the planning and maintenance programs that NCDOT and other states currently have in place. The review highlights infrastructure components and the associated NCDOT units which CAVs have a demonstrated need for. Several NCDOT programs that would potentially be impacted by future infrastructure needs were identified in consultation with St&IC. A survey-based method was used to investigate the infrastructure readiness of public agencies in terms of the anticipated impact (gauge the impacts of CAVs on various units of a public agency), status quo (gauge public agency unit's awareness and capability to accommodate CAVs), planning (gauge resource availability in preparation for accommodation of CAV by public agencies), and training needs (gauge training needs for different units of the public agency to prepare for CAVs).

The second object develops emerging CAV infrastructure and accordingly management tools that should be established by NCDOT for next-generation CAV systems. The research team is proposing a novel edge computing

system infrastructure that embeds the computing capability of roadside units upon CAV infrastructure for ultra-low latency services.

The third and last objective of the project builds on the findings of the first two objectives and recommends enhancements to existing NCDOT programs that will support CAV deployment and advance North Carolina's Readiness for CAVs. On the communication side, our recommendations recognize the communications and network architecture needs, especially considering private- versus public-owned/operated communication infrastructure, that should be fulfilled by NCDOT in realizing next-generation CAV systems.

3.2 Task 1: Literature Review

As the vehicle technology continues to innovate, Connected and Autonomous Vehicles (CAVs) have been the main focus of the automotive industry in the recent years. To date, several automakers such as Tesla, General Motors, Mercedes, and Toyota, etc. have already demonstrated their highly automated driving technologies, and many automotive manufacturers aim to roll out production vehicles with autonomous driving capabilities in the near future [28].

Numerous studies have been conducted to assess the operational and safety benefits of CAVs [199, 215]; in general, these studies indicated that CAVs have the potential to bring about transformative safety, mobility, human productivity, and fuel consumption benefits to the transportation industry, thus are expected to be deployed in the U.S. in the foreseeable future. On the other hand, however, CAVs also have the potential to significantly transform the nation's roadways since they introduce uncertainty for the agencies responsible for the planning, design, construction, operation, and maintenance of the roadway infrastructure [99]. In addition, there are also several technical challenges, such as reliability of data communication, cybersecurity protection, that need to be fully considered.

With these concerns, this report, based primarily on the review of the state-of-the-art, identifies the impacts of CAVs on the roadway design, the traffic control device standardization, and the infrastructure needs to facilitate the state-wide deployment of connected and autonomous vehicles in North Carolina.

3.2.1 Traditional Infrastructure Impacts: One of the critical questions this research effort seeks to answer is whether CAVs raise new requirements for highway geometric design elements and whether they are compatible with existing traffic control devices.

3.2.1.1 Geometry: Geometric design refers to the physical design of a roadway, such as the radii of horizontal curves, the rates of vertical slope changes to be used for connecting roadway segments with different grades, lengths of acceleration and deceleration lanes, etc. In practice, the design of roadway geometry largely depends on the design vehicles and design drivers [12].

Specifically, roadway geometric design needs to consider vehicle performance and human driver capabilities such as sight distance for safe stopping. To date, there have been a number of research efforts that investigated the impacts of the advances in vehicle performance and machine vision systems on geometry design. For instance, [202] discussed the potential impacts of connected vehicles and autonomous vehicles on geometric design of roadways. It was proposed that the physical features (such as vehicle dimension) and mechanical performance of vehicles will influence the controlling criteria of roadways, such as design speed, lane and shoulder widths, horizontal and vertical curve radius as well as superelevation rates, maximum grade, stopping sight distance, etc. In addition, there might be new requirements for traffic signs, striping, as well as other roadside safety devices.

[202, 328] discussed the changes in driver perception-reaction time and eye height on the required sight distances as well as lengths of curves. In general, it was concluded that machines typically have shorter perception-reaction times than human drivers, and thus could significantly reduce the required stopping sight distances and overtaking sight distances. Moreover, machine vision might detect obstacles through the crest of a vertical curve, indicating that the minimum curve radius could be smaller for the same design speed that is designed for human drivers, which could reduce the construction costs. [146] investigated the geometric elements that are directly affected by the elimination of the human driver, including the stopping sight distance (SSD), decision sight distance (DSD), and length of sag and crest vertical curves. This research evaluated the perception-reaction time (PRT) of a full autonomous vehicle which would replace the human driver's reaction time in the SSD and DSD models, and the height of placement of the LiDAR sensor which would replace the driver's eye height in the lengths of crest and sag vertical curves. Similarly, [100, 324, 332] also presented numerical illustrations of the potential changes in the geometric design elements in response to autonomous vehicles. Their research findings, in general, concluded that in comparison with the existing roadway design guidelines, the revised designs are more economical because shorter curves, in general, reduce the construction cost by reducing the required earthen work. In terms of vehicle performance, it is expected

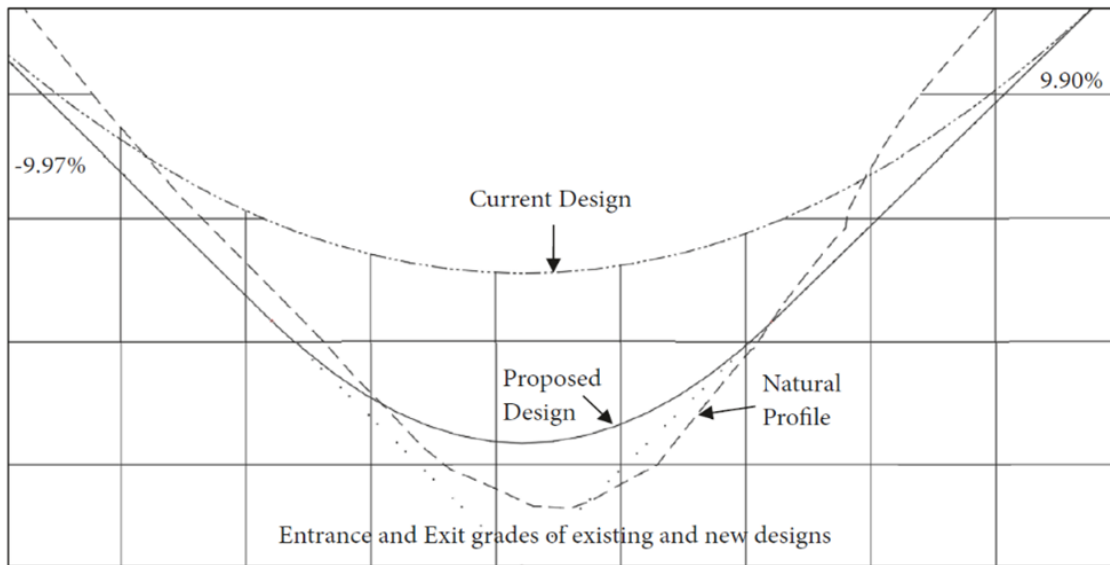


Figure 9. Comparison of sag vertical curve for current design standards and automated vehicles Source: [146]

that connected and autonomous vehicles, with their advanced electric control systems, allow for higher acceleration and deceleration rates [328]. Acceleration rate has the potential of impacting the design of acceleration lanes for freeway on-ramps and the maximum rate of upgrades; deceleration rate is a key factor for determining the length of deceleration lanes for freeway off-ramps and turning lanes, maximum downgrades, stopping sight distances, and the design of horizontal and vertical curves. Comparisons of SSD under various PRT and maximum deceleration rates are presented in Table 4; a graphical illustration of the sag vertical curve for current design standards and automated vehicles is presented in Figure 9.

Table 4. Stopping sight distance under various perception-reaction time and maximum deceleration rates

Design Speed (mph)	Max Deceleration = 11.2 ft/s ²						Max Deceleration = 14.8 ft/s ²	
	PRT (s)	SSD (ft.)	PRT (s)	SSD (ft.)	PRT (s)	SSD (ft.)	PRT (s)	SSD (ft.)
40	2.5	300	1	210	0.5	185	0.5	145
50	2.5	425	1	315	0.5	275	0.5	220
60	2.5	565	1	435	0.5	390	0.5	305
70	2.5	730	1	575	0.5	520	0.5	410

Some research investigated the potential impacts of vehicle platooning technology on highway geometry design. [302] discussed the impacts of vehicle platooning technology on highway geometric design, and pointed out that although the existing freeway infrastructures do not necessarily need to be modified to accommodate vehicle platoons, the interactions between the human factors and the new technologies may directly impact the traditional guidelines for freeway design, such as vehicle platoons might reduce the minimum length requirements and increase posteriori design speeds for all curves. [198] investigated the impacts of truck platooning on the operation and geometric design of freeway on-ramps. It was found that the weaving length between the entrance and the exit ramps is a factor for truck platooning. To minimize the impacts of truck platooning on traffic operations, the research recommended selecting corridors with weaving sections longer than 1,000 ft. for the deployment of truck platooning.

In summary, existing research pointed out that the elimination of human drivers through a fully autonomous vehicle fleet is expected to impact the geometric design criteria of highways, such as the SSD, DSD and length of sag and crest vertical curves. It is expected that the future geometry design standards tend to be more economic and will reduce environmental impacts through smaller cut and fill volumes [146].

3.2.1.2 Signs and Markings: The operation of AVs/CAVs largely depends on the readability of the traffic control devices (TCDs) by the machine vision sensors. In current practice, most AVs operating on different testbeds worldwide are not digitally connected (such as through DSRC or 4G/LTE) with the TCDs, partly because the AV sensors cannot entirely rely on V2I connection due to the latency in communication. Hence, AV sensors primarily rely on computer-vision or LiDAR technologies to read messages from the TCDs ([114, 267]). To support the future

deployment of CAVs, one of the most critical challenges that will be faced by State DOTs is to ensure the TCDs (such as roadside signs and pavement markings) are appropriately installed and well maintained, such that AVs can operate safely and effectively [110].

An early study conducted by [232] discussed the requirements of road infrastructure for highly automated driving. The research concluded that the main infrastructure challenges for automated driving systems (ADS) are: complex urban driving conditions, temporary work zones, and low visibility due to adverse weather condition. Specifically, lane assistance systems call for high visibility and quality of lane markings, and speed control systems require clearly visible traffic speed signs. Later, [151] summarized the infrastructure need and cost for the prevailing advanced driver assist technologies, as shown in Table 5. The research concluded that under normal operational conditions, some vehicle-based technologies, such as adaptive cruise control and blind spot monitoring, do not require particular infrastructures. Some infrastructure-based technologies, such as lane departure warning and lane keeping, require clear lane marking and traffic signs, because they rely on sensing of these objects to determine the surrounding environment. Other technologies, such as traffic sign recognition, automated assistance in roadwork and congestion, auto-valet parking and driverless cars, will require the most infrastructure changes.

Table 5. Stopping sight distance under various perception-reaction time and maximum deceleration rates

#	Vehicle Technology	Infrastructure Need	Infrastructure Cost
1	Forward Collision Warning	None	None
2	Blind Spot Monitoring	None	None
3	Adaptive Headlight	None	None
4	Automatic Emergency Braking	None	None
5	Electric Stability Control	None	None
6	Parental Control	None	None
7	Emergency Stopping Assistance	None	None
8	Automated Operation for Military	None	None
9	Adaptive Cruise Control	None, possible dedicated lane	None/Depends
10	Cooperative Adaptive Cruise Control	None, possible dedicated lane	None/Depends
11	Lane Departure Warning	Lane marks	Low
12	Left Turn Assist	Lane marks	Low
13	Lane Keeping	Lane marks	Low
14	Traffic Jam Assist	Lane marks	Low
15	Traffic Sign Recognition	Traffic sign	Moderate
16	High Speed Automation	Lane marks, Traffic sign	Moderate
17	On-Highway Platooning	Lane marks, Traffic sign	Moderate
18	Automated Assistance in Roadwork and Congestion	Lane marks, Beacons, Guide walls	High
19	Auto-Valet Parking	Parking facilities	High
20	Driverless Car	Lane marks, Traffic sign, Lighting	High

Recently, the U.S. Federal Highway Administration (FHWA) launched a series of presentations regarding the impact of AVs on highway infrastructure. The presentations first highlighted that in current practice, the most important TCD for AV deployment is pavement markings, since both the mature advanced driving assistance systems (ADAS) and the emerging automated driving systems (ADS) need to detect and read markings to guide and position the vehicle. Therefore, pavement markings should be uniform in application and appearance and in a good state of repair to facilitate the vehicle's machine vision system [95]. In addition, the presentations pointed out that the width of longitudinal pavement markings varies across the U.S., as shown in Figure 10. The current MUTCD recommends the width of markings shall be 6 inches for interstate, freeway, expressway, and corresponding ramp interchange markings, and for edge lines on all other roadways with posted or statutory speeds of 55 mph or more and an ADT of 6,000 vehicles per day or greater [304]. Moreover, the FHWA presentation discussed the requirements of pavement marking appearance to accommodate machine vision systems, such as using 6-inch-wide pavement markings to improve the readability of the markings. Some other findings on pavement marking appearance include daytime appearance is just as important as nighttime, and daytime contrast on light colored pavements is particularly helpful for machine vision detection [95].

In terms of traffic signs, the FHWA presentations indicated that the current optical cameras and machine vision systems have limited resolution and range in comparison with some human drivers, thus will be confused by damaged, faded, or noncompliant signs. Moreover, standardization of traffic signs, in terms of content design and mounting location, can improve reliability of detection by reducing complexity of machine vision processing. Besides, it was found that digital signing may be challenging for in-vehicle camera systems, but this may not be a problem for CAVs since the I2V communication technologies allow for directly sending the information displayed on the digital

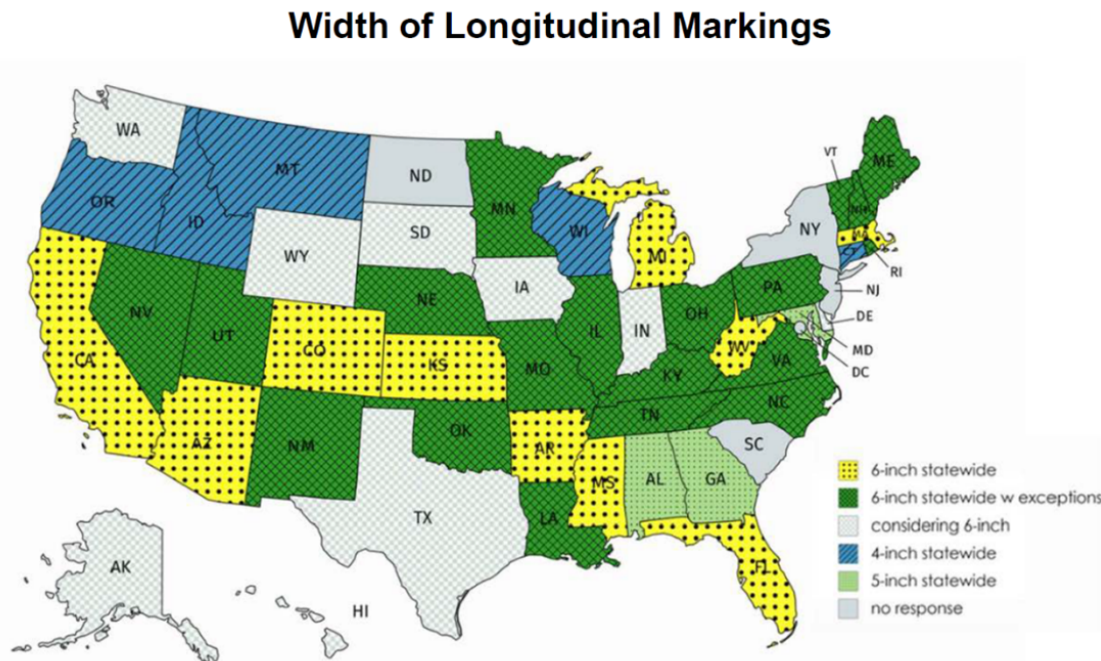


Figure 10. Width of longitudinal pavement marking in the U.S.

signing board to the vehicle [95].

In summary, the recent deployments of AVs have been made possible because their signs and markings detection algorithm has been trained with a giant archive of images of different objects. Yet, transportation agencies should take necessary steps to maintain a certain standard of the TCDs so that those are visible even during low visibility conditions. For instance, the Georgia Department of Transportation has recently deployed special lane markings to delineate all lanes on a 13-mile stretch of I-85 (named The Ray). The Ray had been equipped with other CV features, but the introduction of this new “refractive bead technology” is notable in terms of AV operation. Other TCDs requiring a significantly high standard of visibility for AV operations during both dry and wet conditions are stop signs, pedestrian crossing signs, and work zone signs. A relevant manufacturing company, called 3M, is promoting its new technology for designing both regular and special road signs (e.g., work zone and incident). They claim that their products can maintain a particular reflective index, even during wet and low visibility conditions, so that the AV sensors can reliably read them [1].

3.2.1.3 Traffic Signals: Taking advantage of the Infrastructure to Vehicle (I2V) communication technology, it is expected that the future traffic signal controller can directly send signal timing information to connected and autonomous vehicles. A conceptual illustration of the connected signal operation is presented in Figure 11.

Based on this conception, [209] developed a signal-head-free intersection control logic that aims to maximize the intersection throughput. The research proposed a stochastic look-ahead technique based on the Monte Carlo tree search algorithm to determine the near-optimal actions (i.e., acceleration rates) for CAVs to cross intersections without any movement conflict. It was assumed that when a vehicle approaches the intersection, basic safety messages will be captured through a reliable wireless connection. Then, the maneuver for each CAV was designed to allow the CAV traveling at its desired speed for a fixed time horizon until it receives recommendations from the intersection controller to change its trajectory. Simulation results indicated that this proposed approach could completely eliminate traffic collisions at intersections and significantly reduce travel time by up to 83.7 percent. The conceptual illustration of the proposed signal-head-free intersection operation is presented in Figure 12.

Another key research direction has been focused on the interaction of CAVs and vulnerable road users, such as pedestrians and bicyclists. This is mainly because pedestrians and bicyclists, unlike vehicles, do not need to maintain any standard regarding their visibility at night. Consequently, detecting these users might be challenging for machine vision sensors. Furthermore, jaywalking is common in many places. In addition, if the AV operation is forgiving, i.e.,

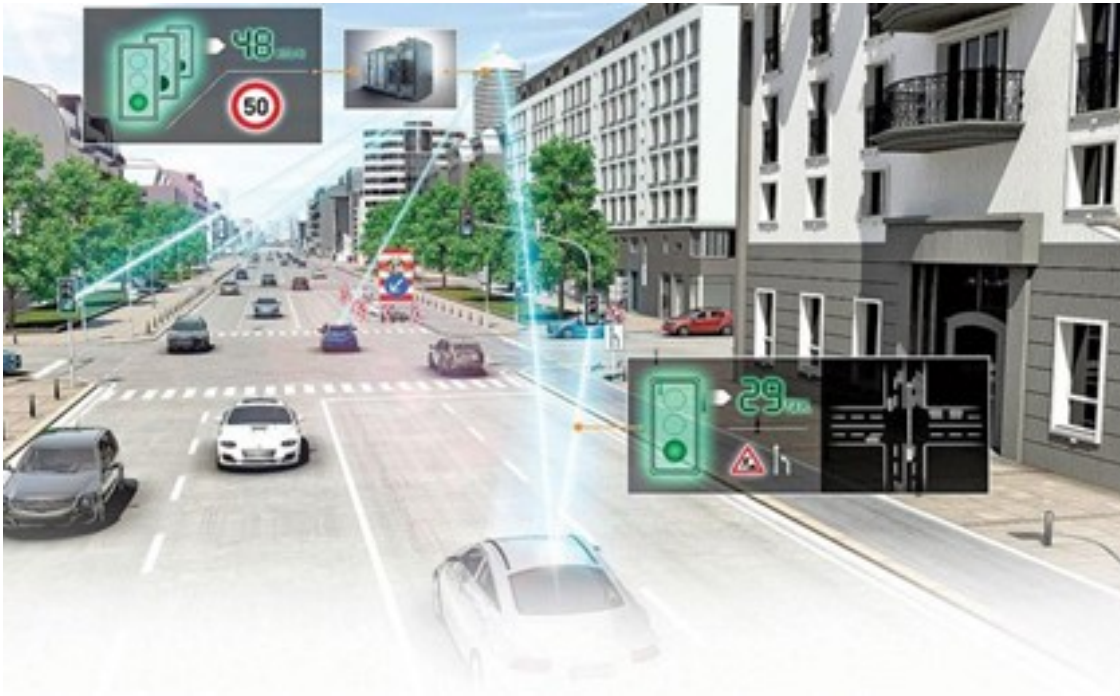


Figure 11. Illustration of Infrastructure to Vehicle (I2V) communications Photo Source: [289]

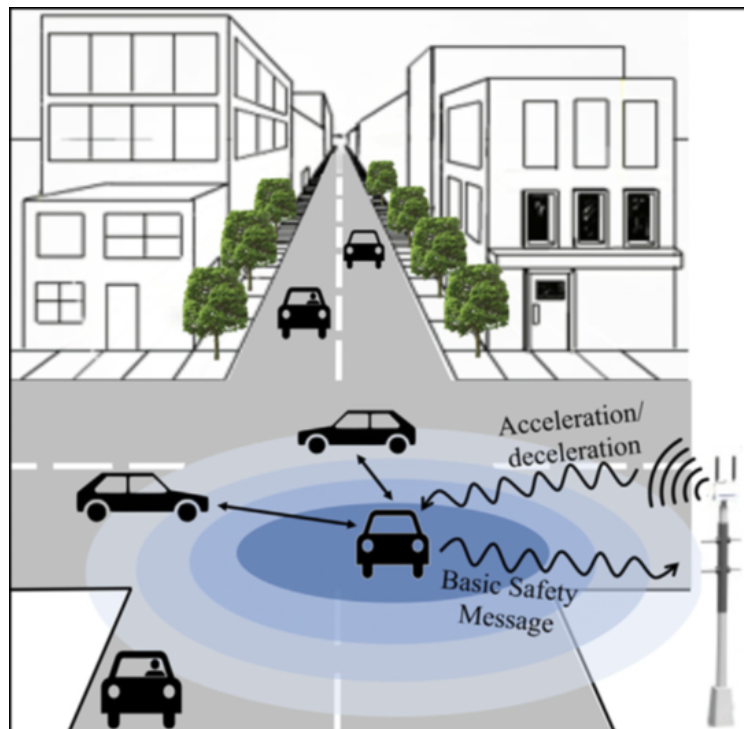


Figure 12. Illustration of Cooperative traffic control in the neighborhood intersection Source: [209]

AVs always yielding to pedestrians and bicyclists, then criminals may take advantage and pose a safety threat to the AV riders [124]. [272] discussed ten such concerning issues related to AV-pedestrian/bicyclist interactions. Among these, the issue of detection, right-of-way determination, passing bicyclists, and picking up and dropping off riders. The recent research addressing these issues is discussed below.

[96] proposed to use flashlights at crosswalks to signal activities of such users to ease the technical complexity related to detecting pedestrians and bicyclists by AVs. Since this technique has not been adopted ubiquitously, some AV operation systems are relying on detecting bicycle lanes instead of bicyclists [165], which is insufficient in the absence of such facilities.

The issue of determining the right-of-way between AVs and pedestrians/bicyclists emerged from the communication gap between them. In the case of traditional vehicles, the leading cause of pedestrian crashes is drivers failing to yield to pedestrians [274]. Furthermore, a large part of the communication between vehicles and pedestrians is bridged by eye-contact or hand-gesture, which for AVs would be a challenging task. The current human-machine-interface of AVs must learn these communication schemes [272].

Other challenging aspects of AV-pedestrian/bicyclists interaction is passing bicyclists and AVs dropping-off and picking-up riders. These issues also arose due to the communication gap between these two user groups. When passing a bicyclist, AVs need to maintain a minimum lateral distance from the bicycle [154]. However, the vision-based algorithm of the AV sensors needs to be developed further to ensure full compliance with this rule [31, 165]. Similarly, when an AV attempts to park by crossing a bicycle lane, its sensors must decide a safe option between waiting for a bicycle (if a bicycle is present on the lane) to pass or maneuver around the bicycle.

3.2.2 Emerging Infrastructure Impacts

3.2.2.1 Advanced Intelligent Transportation Systems (ITS): Intelligent Transportation Systems (ITS) introduce new and innovative technologies to the transportation and traffic management systems for enhancement of mobility and safety. With the advent of connected and automated technologies, ITS concepts and tools are becoming more refined, complicated, and powerful. As the traditional components of the transportation system are being replaced with more automated/connected ones (such as the continued introduction of connected and automated vehicles into the system), the gain from ITS tools are expected to drastically increase.

The United States Department of Transportation (USDOT) is the decision making and development body that has produced a national ITS architecture that provides a common framework for planning, defining, and integrating ITS and CAV technologies into transportation systems. The developed architecture is dynamic in nature and can be adapted to meet the needs of all the stakeholders. To better provide guidelines and streamline efforts, USDOT has developed a tool called the Architecture Reference for Cooperative and Intelligent Transportation (ARC-IT) [2]. The ARC-IT tool, illustrated in Figure 13, provides a common framework to agencies for planning, defining, and integrating ITS. It is an established and industry-standard product that encompasses contributions of all ITS communities. ARC-IT brings together, standardizes, and improves National ITS Architecture and Connected Vehicle Reference Implementation Architecture (CVRIA), as it was previously known. ARC-IT's structure contains four main components: 1) service packages, 2) views, 3) methodology, and 4) security. The Service packages deal with pieces of the architecture that address a specific service, such as traffic signal control. The Views component provides view-specific content. ARC-IT has four view layers of enterprise (describes relationships between organizations), functional (describes logical interactions between functions), physical (describes connections between physical objects), and communications (describes layered protocols facilitating data exchange between physical objects). The Methodology component sheds light on the how-to of the structure of the architectures. Lastly, the Security layer explains how security concerns are addressed throughout the architecture and provides reference to the state-of-the-art security contents.

3.2.2.2 V2X and CV Testbeds

3.2.2.2.1 V2X: V2X is a vehicle-to-everything communication channel between a vehicle and the outside surroundings. It has many parts, starting with vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I) and vehicle-to-network. The application of V2X is infotainment technology such as Bluetooth, satellite radio and music player. Below Figure 14 is the structure of V2X communication by the reference of the published article [147], where they define two communication structures. V2X taken from the VANETs (vehicle ad-hoc networks), which uses DSRC (dedicated short-range communication). DSRC is a defined standard of wireless access from IEEE 802.11p and higher layer standard from IEEE 1609, which defines the standards, structure as well as the channel of communication between V2V & V2I. Moreover, it consists of a vehicle inside and outside unit, on board unit and roadside unit, respectively. The components of on side units are: 1) communication control, which interconnects the

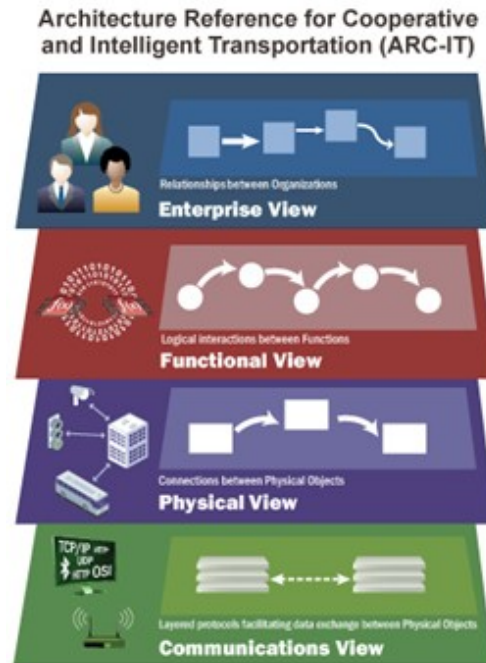


Figure 13. Architecture of cooperative and intelligent transportation Source: [312]

vehicle interior and exterior; 2) neighboring vehicle details obtained from the routing table; and 3) map dataset that stores the road condition and traffic flow data. Whereas, in roadside units track information of all cars through wireless or wired network via location servers, and are commonly used for V2I communication. On the contrary, cellular vehicle-to-everything (C-V2X) uses long-term evolution (LTE) mobile cellular networks,. C-V2X has a longer range than DSRC, and it has a significant improvement in performance with obstructions.

3.2.2.2.2 V2I: Research and development on vehicle communication (V2V, and V2I) have received special attention from different parties in the past few years. The United States Department of Transportation's (USDOT) ITS movement and the European Union are two of the governmental stakeholders that have heavily invested in the research and development of V2I with the main focus on safety enhancements.

In V2I communication, vehicles send and receive data via the fixed roadside infrastructure components called Roadside Units (RSU) that act as base stations and are placed on each roadway segment. RSUs communicate with the vehicle on-board units (OBU) to send and receive information on traffic stream conditions from and to vehicles located in their immediate environment [50]. Presence of V2I not only improves safety, but also efficiency, reliability, and security.

To enable communications and relevant applications, vehicles should be equipped with on-board units (OBU) that enable them to communicate wirelessly as shown in Figure 14. Intersections/roadways should be equipped with RSUs. The communication protocols that connected vehicles use to communicate with the infrastructure must be fast, reliable, secure, private, and interoperable [240]. An outcome of the previously mentioned efforts by the governments and OEMs has been the standardization of the communication protocols utilized for V2I communications. Some of the readily available and already deployed standards are DSRC [54], WAVE [311], and LTE-V2X [8].

DSRC, derived from the IEEE 802.x family, uses licensed spectrum at 5.9 GHz with seven 10 MHz bandwidth channels. The DSRC service comprises both V2V and V2I communications, with the primary goal of enhancing the travelers' safety [54]. DSRC, however, suffers when it comes to providing the fast communication, which is necessary for vehicular networks. To promptly address these issues, DSRC efforts were moved to IEEE802.11 p WAVE [311]. WAVE employs Orthogonal Frequency Division Multiplexing (OFDM) to break and guide signals into smaller channels. LTE and 5G are two other mediums through which V2I communication can take place and are becoming the desired mode of V2I communication. The advantages include improved network capacity, wider coverage and greater mobility support. The higher latency compared to WAVE, however, is one of the drawbacks of LTE (Remy et al., 2011).

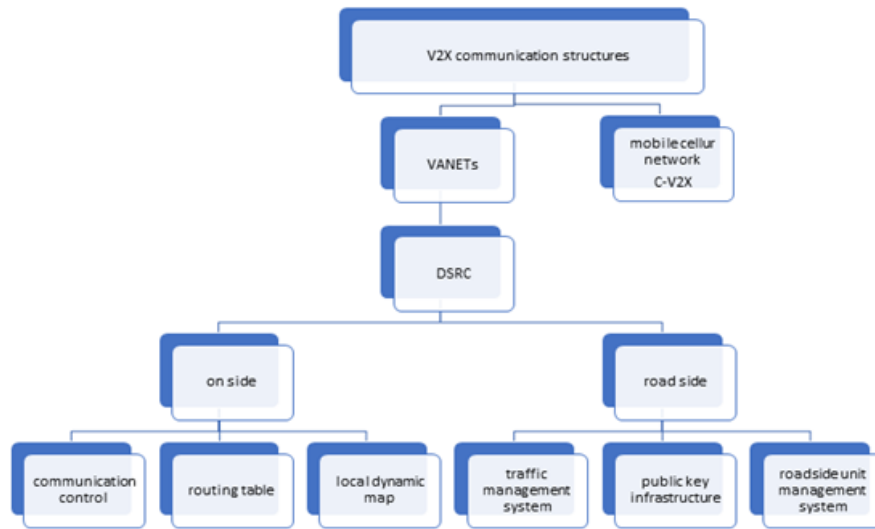


Figure 14. Structure of V2X communication



Source of Photo: USDOT. In this figure the intersection can communicate with the equipped vehicles and share information such as its physical geometry and current signal phase and timing. Similarly, the vehicles share their location, speed, heading, acceleration, and other attributes to the RSUs. This communication and messages enable the traffic controller optimize vehicle flows and minimize unsafe situations

Source of Photo: USDOT. In this figure the intersection can communicate with the equipped vehicles and share information such as its physical geometry and current signal phase and timing. Similarly, the vehicles share their location, speed, heading, acceleration, and other attributes to the RSUs. This communication and messages enable the traffic controller optimize vehicle flows and minimize unsafe situations

Figure 15. Portraying Communication between OBUs and RSUs at signalized intersection

Source of Photo: USDOT. In this figure the intersection can communicate with the equipped vehicles and share information such as its physical geometry and current signal phase and timing. Similarly, the vehicles share their location, speed, heading, acceleration, and other attributes to the RSUs. This communication and messages enable the traffic controller optimize vehicle flows and minimize unsafe situations

V2I applications include both safety (e.g., driver assistance and hazard warning) and non-safety (e.g., air pollution monitoring and on-board entertainment) related applications. The non-safety applications can be categorized into two classes of traffic efficiency and management and entertainment along with personalized applications. Table 6 [94] shows some of the V2I applications along with the required message and its handler.

Table 6. V2I Messages by Application and Message Handler

	Position Correction Message Handler	Map Message Handler	BSM/ Approaching Vehicle Aggregator	Traffic & Rail Signal Message Handler	Local Weather and Road Surface Message Handler (Map Overlay)	Roadside Signage DMS Arbitrator	Local/Back Office User Interface
	Position Correction Message	Local Map Message Traffic Signage Data	Approaching Vehicle Mess BSM (V2I) Vehicle Weather Data Oversize Vehicle Detection	SPaT Messages (SRM, SSM) Rail Crossing SPaT Ped Crossing SPaT	Local Weather Message Road Surface Condition Mess Dynamic Roadside Sign Mess	Installation, Configuration, Maintenance	
INFLO-Queue Warning (Q-WARN) (TME Based)	✓	✓	✓	✓	✓	✓	✓
INFLO-Speed Harmonization (SPD-HARM) (TME Based)		✓	✓	✓	✓	✓	✓
Intelligent Traffic Signal System (ISIG)	✓	✓	✓	✓	✓	✓	✓
Emergency Vehicle Priority	✓	✓	✓	✓	✓	✓	✓
Transit Signal Priority	✓	✓	✓	✓	✓	✓	✓
Freight Signal Priority	✓	✓	✓	✓	✓	✓	✓
Pedestrian Mobility		✓	✓	✓	✓	✓	✓
Eco-Traffic Signal Timing;	✓	✓	✓	✓	✓	✓	✓
Eco-Approach and Departure at Signalized Intersections;	✓	✓	✓	✓	✓	✓	✓
Eco-Traffic Signal Priority; and	✓	✓	✓	✓	✓	✓	✓
Eco-Driving - Connected Eco-Driving.	✓	✓	✓	✓	✓	✓	✓
Dynamic Low Emissions Zones	✓	✓	✓	✓	✓	✓	✓
Dynamic Eco-Lanes	✓	✓	✓	✓	✓	✓	✓
Enhanced Maintenance Decision Support System (MDSS).	✓	✓	✓	✓	✓	✓	✓
Information for Maintenance and Fleet Management Systems.	✓	✓	✓	✓	✓	✓	✓
Weather-Responsive Traffic Management.		✓	✓	✓	✓	✓	✓
Motorist Advisories and Warnings.		✓	✓	✓	✓	✓	✓
Information for Freight Carriers.	✓	✓	✓	✓	✓	✓	✓
Information and Routing Support for Emergency Responders.	✓	✓	✓	✓	✓	✓	✓
Red-Light Violation Warning (RLVW)		✓	✓	✓	✓	✓	✓
Stop Sign Gap Assist (SSGA)		✓	✓	✓	✓	✓	✓
Curve Speed Warning (CSW)		✓	✓	✓	✓	✓	✓
Stop Sign Violation Warning (SSVW)		✓	✓	✓	✓	✓	✓
Railroad Crossing Violation Warning (RCVW)		✓	✓	✓	✓	✓	✓
Spot Weather Information Warning (SWIW)		✓	✓	✓	✓	✓	✓
Oversize Vehicle Warning (OVW)	✓	✓	✓	✓	✓	✓	✓
Reduced Speed Zone Warning (RSZW)	✓	✓	✓	✓	✓	✓	✓

3.2.2.2.3 CV Testbeds: In many existing CV testbeds, CV technologies are linked with traditional TCDs primarily through vehicle-to-infrastructure (V2I) technologies. The infrastructure requirements for implementing CV technologies mainly depend upon the CV application [51]. Hence, this discussion is divided by different applications of these CV testbeds. Applications of the CV-TCD connection at the existing testbeds targeted to improve intersection safety include pedestrian crossing alert [262]; THEA, 2018; Pape and McMracken, 2016), red-light violation alert [355], assisting left-turns in the case of permissive phasing [212], and wrong-way entry alert [27]. Applications of the CV-TCD connection at the existing testbeds targeted to improve intersection mobility and emission include traffic progression [27], transit signal priority and advisory speed recommendation.

Note that several of these applications require the active engagement of the TCDs, such as a signal controller setting changes when implementing transit signal priority. On the other hand, some of these applications do not require

an active engagement of the TCDs, such as pedestrian crossing or wrong way entry alert. However, even for the latter cases, the communication and sensing units exchange data associated with the TCDs (e.g., data on crosswalk usage for pedestrian alert and data on lane designations for wrong way alert). Hence, case studies associated with all these CV applications are discussed here.

Transit and Freight Signal Priority (TSP)

This CV feature provides preference to transit (or freight or emergency vehicles) at signalized intersections through a green extension or an early start of green for an approaching transit [128]. In general, this feature works according to the following algorithm [27]: a connected transit approaching a connected intersection requests the signal priority, along with its basic safety message (BSM), in the form of a signal request message (SRM). The road-side unit (RSU) receives and transmits this message to the central server, which is linked with the transit scheduling server. Based on the transit's BSM and the intersection's geometry (MAP) and signal phasing and timing (SPaT) data, the server computes the intersection clearance time for the transit given the current phasing condition. Next, the server evaluates this time against the transit's planned schedule. If the transit is either on-time or early, the signal phasing remains the same. Otherwise, an early green or a green extension is provided to the phase serving the incoming transit. This outcome is sent to the signal controller for implementation. This communication between the transit and the RSU is typically set up over a dedicated short-range communication (DSRC), WiFi, or LTE network.

Freight signal priority and emergency vehicle signal preemption also follow a similar process to transit signal priority [203]. However, for the former cases, data processing can be less intensive if the computation for evaluating the scheduled time is skipped.

The signal priority program is a critical part of the CV pilot deployment program of USDOT. As reported by the Tampa Hillsborough Expressway Authority [27], TSP was implemented at three signalized intersections along a corridor. Here, the main server got a feed of the transit schedule from the HART transit server. In addition to the transit-to-RSU connection, THEA leveraged an RSU-to-PID (personal information device) connection to inform the connected pedestrians if a transit's trajectory is going to conflict with the pedestrian crossing trajectory.

[203] presented a description of the required instruments for implementing this feature on the CV testbed located at El Camino Real, CA. This testbed encompasses a series of 11 consecutive signalized intersections. The connected intersections are equipped with RSUs that broadcast and receive messages over both DSRC and a cellular network (4G/LTE). Their signal priority program's efficiency was evaluated in terms of reduction in travel time, delay, and the number of stops for several test transits. It was found that the transit average travel time, number of stops, and stopped delay through the entire testbed corridor reduced by 14.1%, 7.3%, and 12.5%, respectively, when the signal priority program was active.

Pedestrian Safety Alert at Intersections

This CV feature is tested at several existing CV testbed intersections [27,51,242]. In addition to a pedestrian push button, the crosswalk is equipped with a sensing device that detects pedestrian activities. The sensor sends pedestrian activity information, including their heading direction and speed, to the data processing server. The server also receives the approaching CVs' BSMs. These data are fused in real-time to predict possible conflicts and necessary alerts are sent to the CVs.

In many CV programs, pedestrians are equipped with a personal information device (PID) [27,242,335]. A PID can be in the form of an active cell phone app. In such cases, the PID also receives a warning message about any potential conflict. For a faster process, the infrastructure connection is skipped, and the conflict is determined solely through the position and heading information of the connected pedestrians and vehicles [335]. This approach is very efficient when the sensor to detect pedestrian activities becomes obsolete due to restricted visibility at nighttime or inclement weather conditions. However, the major issue with this approach is that the participating pedestrians must carry a hand-held device or keep the necessary app active all the time. Hence, this approach is applicable to the actively participating pedestrians only, which can be a mere fraction of the total pedestrian volume at a crosswalk. This issue can be avoided if the sensor can provide reliable data related to pedestrian activities to the server and the alert is sent to the CVs without a significant communication latency. In this regard, several studies (Rahman et al., 2019; Matti et al., 2017; Kwon et al., 2016) were carried out to test LiDAR, radar, and a combination of video camera and vision-based algorithm to detect pedestrian speed and heading direction. Using a video camera is the most cost-effective solution; however, its benefit comes with a higher latency (vision-based detection algorithms are computationally intensive) and disuse in poor lighting conditions. Using LiDAR instead of a camera increases detection accuracy and reduces communication latency, but its performance is poor during inclement weather conditions. Also, LiDAR is more expensive than cameras. On the other hand, radar works reasonably even during poor weather and lighting conditions.

Advisory Speed Recommendation

TCDs at intersections incur additional delays and number of stops to the vehicles and emissions to the environment. However, with the advent of CV technologies, it is possible to minimize these adverse effects of TCDs by providing advisory speed recommendations. The number of stops and control delay for the approaching CVs can be minimized by providing speed guidance estimated based on real-time SPaT (from the approaching signal), BSM (from the CVs), and other vehicles' dynamic (from additional sensors) data. Thus, the driver may avoid maneuvers like extreme acceleration and deceleration, which are the major sources of traffic emissions.

[158] demonstrated a very simple yet efficient application of recommending advisory speed at a corridor of signalized intersections located in Woodbridge Township, NJ. The 6.5 miles-long corridor houses ten signalized intersections. The approach is simple from the perspective that the infrastructure requirement is minimal. The signal controllers are connected to the NJDOT arterial management center (AMC). The controllers push real-time SPaT and vehicle actuation data toward the AMC, which transfers the data to the NJIT In-Vehicle Traffic Signal Advisory System (ITSAS) database center. NJIT ITSAS database also receives the speed, acceleration, and GPS position data from an Android-based App installed in the participating CV drivers' cellphones through a cellular network connection (3G/4G/LTE). The NJIT ITSAS fuses this data, computes the advisory speed, and sends the output back to the cellphone app. The communication delay observed in the field was below 1 second, which, for this research, was within a reasonable limit.

Hence, the primary infrastructure elements needed to implement this CV feature are i) sensors that are typically installed at intersections to detect the presence of all vehicles; ii) a stable connection between the traffic signal controller and the AMC; iii) a stable connection between the AMC and the database; iv) the database also needs to store historical signal timing data for each intersection so that in the case of an actuated or semi-actuated controller, it can estimate the signal timing based on the historical data; v) a stable cellular connection between the CV's cellphone and NJIT database.

The major disadvantage of relying on cellular connection instead of a local edge unit (e.g., a DSRC) is that the delay is significant and a loss in cellular connection would shut down the process. However, this delay and outage of connection were presumed not to create any safety hazard since the application of this CV technology was only to provide an advisory speed. A field test carried out at different times of the day with CVs with and without the speed advisory app showed that a significant saving in travel time is possible.

[239] also conducted a field test of recommending advisory speed to both CVs and CAVs. However, their testing was limited to an isolated intersection serving only a few test vehicles. The connected infrastructure, consisting of an RSU linked with a cloud server, receives BSMs from the participating vehicles over a DSRC network. The position and speed of the traditional vehicles are estimated using a Doppler-based radar installed at the intersection. The radar can detect the approaching vehicle in the front of a traffic stream from 500 ft away from the stop bar. Data from both the radar and BSM are sent to the server for feeding the computational platform. By fusing MAP data, BSM data for the CVs and CAVs, and radar-sensor data for all vehicles, the server distinguishes TVs from AVs and CAVs and estimates their relative positions, including lane IDs. The server incorporates SPaT data to estimate the advisory speed for each CV and CAV. The recommended speed is then transmitted from the RSU to the OBU of the participating vehicle over the DSRC network.

Assisting Left-turn Movement

With a permissive or protected-permissive signal phasing, the left-turn movements at a signalized intersection may face difficulty to accept a safe gap, particularly if the opposing thru movement has a high traffic volume. In this regard, CV technology can provide necessary guidance to left-turning vehicles. In general, the process is [212]: an RSU receives position, speed, and acceleration data from CVs at both the subject left-turn and opposing through approaches. A sensor detects the position and speed of the first vehicles in the stream coming to these approaches. A data processing unit receives these two data along with the real-time SPaT information from the signal controller. By fusing all this information, the unit computes the likelihood of any collision between the left-turners and the opposing through traffic. It then generates a binary message—either cross or do not cross the intersection—for the left-turning vehicle in the front of the queue.

[212] used a collision warning radar system (EVT-300) to detect the approaching vehicles' position and speed. They disseminated the final advisory message in two ways, one through a LED-based, looming road-side sign and another through a display installed at the dashboard of the participating CV at the front of the left-turning queue. No significant difference regarding the compliance of the drivers to the displayed message was found between these two methods.

Traffic Progression

Progression of traffic through a series of signalized intersections is important for maintaining a satisfactory

level of service through a corridor. The signal phasing offsets for such a series of intersections need to be optimized so that the vehicles stop the least number of times. An essential parameter for estimating the optimized signal offset is the progression speed of the traffic stream, which is often estimated on the basis of the posted speed limit. With the advent of CV technologies, it is now possible to estimate the vehicles' position and speed so that traffic can progress through a series of intersections smoothly.

Compared to other CV applications discussed above, such as pedestrian conflict estimation and left-turn assist, improving traffic progression is less computationally intensive [27]. According to this CV-based feature [27], the CV(s) in a traffic stream sends BSMs to the RSUs, which are pushed toward a master server. The master server also receives the total vehicle count and the overall traffic condition data from traditional road-side sensors. The server fuses SPaT data from each intersection and estimates the optimized offset. It sends necessary signals to the controller for adjustment and re-synchronizing the clock. This feature was implemented in the THEA CV testbed [27] in Florida along Meridian Avenue, Florida Avenue, and a part of N Nebraska Avenue.

Wrong-Way Movement Alert

Wrong-way entries are a very rare event; however, the resulting crashes have the highest severity rate compared to all other crash types [322]. CV technologies can play a pivotal role in alerting both a CV making a wrong-way turn, the TMC operator, and the law-enforcement agency. In this system, a connected intersection sends the SPaT and MAP data to all CVs' OBU through an RSU. The MAP data contains the direction for each lane. The OBU uses the vehicle's GPS data to determine if the vehicle's direction is conflicting with that of its lane position. If yes, the OBU immediately produces a warning message. At the same time, a computing unit also uses a "wrong way entry application" to detect a wrong-way entry by a CV using its BSM, SPaT, and MAP data. If a wrong-way entry is detected, an alert is sent to the TMC operator and to the law-enforcement agency.

THEA, as a part of their CV testbed, implemented this technique at a few interchanges that connected the Reversible Expressway Lane [27] with the arterials. All lanes of the REL serve the westbound traffic in the morning peak and the eastbound traffic in the afternoon peak [27]. Due to this reversible nature of the expressway, there is a high chance of a wrong-way event. This fact motivated the THEA authority to test a wrong-way detection application for the participating CVs at this expressway.

3.2.3 Communications: In the literature, there exist several works [75, 99, 105, 173, 270, 343] addressing diverse aspects of vehicular networks. A downlink multicasting scenario for close-proximity vehicles was acknowledged in [270]. The author, first, created a group of vehicles as a hotspot and served the hotspot users from a single transmission point. [343] proposed a vehicle-to-vehicle (V2V) radio resource management (RRM) method, where they used deep reinforcement learning (DRL) to scrutinize the reuse of the uplink radio resources for effective V2V communication. A similar approach was also considered by [173], for V2V applications using multi-agent RL (MARL). [75] considered RRM for vehicular networks. Although the authors considered virtual cell member association and RRM in their problem formulation, they did not consider user mobility.

[99] proposed a joint admission control and resource management scheme, for both static and vehicular users. Using the Lyapunov optimization technique, the authors showed a way to increase network throughput from the traditional network-centric approach. [105] considered a Q-learning based solution for V2V communication. They used a two-staged learning process for minimizing overall latency and maximizing the network throughput. [247]: a throughput-optimal vehicular edge network for highway transportation were considered that achieved a maximum weighted sum rate using RL.

In autonomous driving, typically, each vehicle brings a large number of sensors onboard [62, 299, 300]. This leads to a tremendous collection of measured data that needs to be processed as quickly as possible. However, the processing capability is understandably lower in the vehicle's onboard units (OBUs). To ensure reliable and viable autonomous driving, therefore, if not all, at least a large amount of its sensed data need to be offloaded to the edge servers. Multi-access edge computing (MEC) is another enabler technology that is expected to play pivotal roles in real-world V2X communication [251]. Different leading mobile operators, vendors, and government organizations are heavily investing in MEC for future generation V2X communications. The core idea of MEC is to offload large computational tasks to the MEC servers residing in proximity to the users. This novel idea intends to minimize the delay by bringing the computation resources nearer than the far-away cloud servers. Not to mention, regardless of computing platform, user's data need to be offloaded using the physical network infrastructure. Besides, unlike the downlink data transmission where the BS can use higher powers to increase the SINR of some users, the uplink scenario is different as the user-side transmitter has limited battery power, in general. Therefore, fast, efficient, and reliable data offloading is one of the fundamental aspects of MEC and other alike platforms.

Over the past few years, we have noticed significant contributions in V2X communication and vehicular edge computing domains from traditional network-centric viewpoints [62, 90, 145, 299, 300, 322]. However, the importance of fast and reliable data offloading is often ignored in the existing literature. A novel realistic offloading was investigated by [62]. Using a real-world simulation environment, the authors have shown the efficacy of fast data offloading in autonomous driving from a typical network-centric paradigm. Similar approaches were also addressed by [299, 300, 327] proposed a non-cooperative data offloading framework for V2I communication from the traditional network-centric prospect. Although the authors have shown some excellent ideas, they only solved the offloading game for a single time slot. Therefore, the problem of fast mobility in V2I communication was not properly addressed. Besides, to solve a long sequential game with the proposed distributed way may not be suitable. [90] proposed a brilliant three-layered computing platform. Following the classical queueing theory, the authors used a heuristic algorithm to maximize a social welfare metric from a typical one-to-one mapping perspective. Another distributed deep reinforcement learning (DRL) solution for task offloading was proposed by [145]. Particularly, the authors used multiple deep neural networks (DNNs) to train their model that aims to maximize the reward from a network-centric approach.

However, we have not noticed very depth user-centric fast data offloading studies in the literature. We acknowledge a few user-centric studies in vehicular network platforms [190, 247, 249, 301, 334, 336, 342, 345, 346], user-centric infrastructure-to-vehicle downlink communication was investigated. [334] discussed user-centric V2I communication from a stochastic geometry perspective. Particularly, the authors derived various closed-form approximations of the outage probabilities for different signal-to-noise (SNR) constraints. [336] used the concept of user-centric virtual cell (VC) that used a similar concept introduced by [204, 269, 270]. The authors assumed that a set of VUs in proximity could be considered as a hotspot (HS). All VUs in such an HS could then receive the same multicast data from the multiple base stations. While this is a novel approach, it will work only when the VUs are intended to receive the same signal.

3.2.4 Cybersecurity: As advances in Machine Learning (ML) and Deep Neural Networks (DNN) bring huge potential to search and develop self-driving cars a reality. Technology advancements in both the software and hardware side opens new doors for huge applications in different domains. For that, many companies are in the race of developing safe and secure autonomous cars (such as Ford, Toyota, NVIDIA, NCA&T and many more). Due to its communication system, more chances of threat surface access to exploit system vulnerabilities for malicious hackers. This paper proposes a survey of different Machine learning based papers related to cyber-attacks on Connected and Autonomous Vehicles (CAV) with presenting threat models and defense techniques. CAV is a transformative technology which nowadays has increased potential in the research area. It helps to reduce traffic congestion, accidents, improves efficiency along with improved quality of vehicular systems. Moreover, with the use of developed technologies such as Machine Learning, Big Data, Internet of Things (IoT), sharing economy can make the huge benefit to turning smart cities with making changes as follows: improves safety, reduce the consumption of fuel, reduce transportation cost, traffic congestion, reduce risk of accidents, improves mobility and accessibility, open jobs and services. The smart cities are achieved by using components such as mobility, good environments, smart economy, lifestyle [34]. If we talk from the beginning of this era, the first research on driverless cars started in 1966-1995 where it was an initial stage of work developed on such a side. The main purpose was to develop the connected cars. Later, the modern vehicles were equipped with advanced driver assistant systems, which pushed a big step to vehicle automation. Recently, with the advantages in artificial intelligent and data science, the era of autonomous driving is approaching at a fast pace.

This development provides a different level of CAV which derives the automation level of a vehicle. It is classified by the Society of Automotive Engineers (SAE) into 6 levels [235], Level 0-5. Level 0, no automation, the driver must perform all the tasks by self. Level 1, driver assistance, driver has full control of it, but some features are included in the design. Level 2, partial automation, is a combination of driver plus added features such as acceleration, steering control by vehicle design but the driver must keep an eye on the environment all the time. Level 3, conditional automation, driver is required but relieved from monitoring the environment all the time but still must be prepared to take command of the vehicle at any time. Level 4, high automation, means a vehicle is capable enough to make decisions under certain conditions with performing all functions but it is possible for a driver to get control over it. Level 5, full automation, vehicle is fully capable to drive in any condition, still the driver can take over the control at any time. These levels describe the brief survey of advancement in technology and summarize that, right now we are in a race of developing levels 4 and 5 [235]. To do so, many companies are racing to impose mobility in CAV. For that they refer to the CASE logo which determines the connected autonomous shared electric vehicles. To achieve four

modules, they are trying to impose new deliverables to the end user. First comes Connected, which refers to delivering new digital experience to consumers with influence data in new ways to modernize operation. Second is Autonomous, which helps to reduce accidents in short term, helps to improve production in the mid term goal and fully manages traffic flow in the long term. Third is Shared, which maximizes the utilization of vehicles and adds the lower rates of transportation to consumers. The fourth one is Electric, which helps to reduce fossil fuels as we can impose the electric engine to autonomous vehicles, and with the addition of it, to some extent, reduce the air pollution.

The above information derived insight of the hardware side but that is successively achieved with the help of advancement in the software side. This advancement of vehicle-to-vehicle communication networks drastically increases the growth of generating more data, which leads to potential cyber threats on CAV. As we know, communication is possible in CAV with the different sensors and electronic units. One such component is ECU (electronic control unit), which is the heart of the communication channel. This unit controls the specific function in vehicles and outside the vehicles with help of connected sensors such as LIDAR, Radar. Lidar stands for light detection and ranging which are commonly used to measure the distance from a variable (such as moon) to earth through laser. It works in rain and fog conditions as well. Whereas radar stands for radio detection and ranging provide sensor input which fed data on current and developing state of vehicle surroundings. It is commonly used to control speed limits, traffic lights, traffic signs, changing lanes, weather forecast and many more. These sensors communicate with the control system of the vehicle via their ECUs over the CAN bus. ECU is able to control different modules of autonomous vehicles, namely brake control, central control, body control, telematic control, speed control, suspension control, general electronic control, and transmission control. These modules provide a vast surface to impose new strategies towards full automation but simultaneously also develop the attack surface for attackers to impose threat in vehicles [251]. Cyber security in computational intelligence means prevention of computer system's function against cyber-attacks. It can damage its software, hardware, and data, and it could be possibly by physically or remotely. Due to its impact on the people, where safety and security is the major concern, it must be considered a high priority and those factors are motivators to conduct research on the cyber security framework of CAV. In the existing literature, there have been defined complex cyber security challenges at the developer side [121]. First, autonomous vehicle characteristics which mean it is difficult to identify all potential attacks before it happens. Second is vulnerability, which is complicated as many functions work together with a variety of different components attached to it. Third is handling of data is difficult, and the fourth challenge is the data communication is performed via Bluetooth, DSRC (dedicated short-range communications) and Wi-Fi, which in turns increases the risk of cyber threats.

[147, 296] discussed the three major categories that introduce cyber attack threats in the autonomous vehicle: control system, component of autonomous driving system and vehicle-to-everything communication. From these three the most popular threat points relate to in-vehicle and communication channels as it deals with data. In addition to the data threats, another safety concern on self-driving vehicles is a vehicle's collision-prevention capability when the vehicle involves cyber-attacks. A brief description of the typical cyber attach threats in the autonomous vehicle is shown in Figure 16.

3.3 Summary

In summary, it is expected that AV/CAVs' advanced control system could significantly reduce the brake reaction time in comparison with human-drive vehicles, which tends to call for a shorter stopping sight distance. CAVs' platooning and communication technologies also produce possibilities for higher speed limits, shorter merge areas and ramp terminals, steeper grades, smaller gap acceptance for turning and crossing vehicles, and shorter turn bays at signalized intersections. In this regard, existing geometric design elements (e.g., horizontal, vertical and cross-sectional elements) that were designed for human drivers could be changed when CAVs replace human drivers. The new roadway design standards might have the potential to ensure optimization of highway geometric design.

In terms of traffic control devices, currently, the AVs are interacting with different TCDs solely through their sensing devices (LiDAR, radar, vision-based). The AV sector still has to wait a long time to communicate with the TCDs over a wireless network that has a sufficient low-latency. However, their sensors appear to have been trained enough to interact with typical TCDs. Furthermore, government agencies and TCD manufacturers are developing standard TCDs to facilitate AV operation. For CAVs, virtual signs provided by I2V communication could provide supplementary information, and more clear pavement markings and roadside traffic signs would benefit both human drivers and machine vision systems.

For traffic signals, it is expected connected signals might eliminate the requirement of signal heads. On the contrary, the interaction of CAVs with pedestrians and bicyclists still appears to be a challenge. Government agencies can play a pivotal role to improve the quality of pedestrian crosswalks and bicycle lanes, but the CAV OEM must train



Figure 16. Cyber attack threats in the autonomous vehicle

their human-computer interface to eliminate their communication gap with pedestrians and bicyclists.

In terms of the deployment of dedicated short-range communication (DSRC)-based communication devices, it was found that there are still several uncertainties such as the compatibility of various DSRC devices produced by different manufacturers. In this concern, the roadside unit (RSU) and DSRC systems should follow a national standard and the systems must be interoperable with the devices on all vehicles. Moreover, the messages sent and received through DSRC should be uniform in all states in the U.S. In addition, the deployment of RSUs should take into account the roadway and traffic features of the sparse, rural areas in the U.S. For instance, providing electrical power to RSUs might be a problem. Furthermore, the optimum number of RSUs to support V2I applications in rural areas is not known yet.

3.4 Task 2: Analysis of Existing Infrastructure and Maintenance Programs to Support CAV Deployment

3.5 Methodology

To understand the impact of CAVs on infrastructure readiness, the research team embarked on a journey to consult with the North Carolina Department of Transportation (NCDOT) to identify the programs within the department that will be impacted by the introduction of CAVs. Among the many units and programs within NCDOT, it became clear that the Intelligent Transportation Systems (ITS), construction, roadway maintenance, Transportation Systems Management and Operations (TSMO), planning, traffic safety, and roadway design were identified as the programs that would be most impacted by the deployment of CAVs. These units and programs are responsible for the backbone of our transportation system, and their smooth functioning is essential for the efficient movement of people and goods. The introduction of CAVs would require changes to the way these programs operate, and it was crucial to understand the implications of these changes.

As the research team delved deeper into investigating the research questions, it became apparent that multiple methodologies would be required to conduct this research. The team considered various approaches, including literature reviews, interviews, focus groups, and case studies. However, after much deliberation, the team settled on using expert surveys as the primary methodology. The reason for this decision was that expert surveys allowed for the collection of detailed and in-depth information from individuals who have expertise and experience in the field of CAVs and transportation infrastructure. The use of expert surveys also allowed for the collection of information from a diverse group of individuals, which provided a more comprehensive and representative understanding of the issue at hand. In this case, the expert survey was conducted among a diverse group of individuals, including transportation engineers, academics, researchers, original equipment manufacturer, and transportation planners, to gather a wide range of perspectives and insights.

Furthermore, expert surveys are particularly useful in situations where there is a lack of existing data or

research on a particular topic, as they allow for the collection of new information and insights. In this case, the expert survey aimed to gather information on the readiness of transportation infrastructure for the integration of CAVs, as well as to identify any challenges and opportunities that may arise with the deployment of CAVs.

Moreover, expert survey also allows for the collection of quantitative and qualitative data, which is particularly useful for identifying and understanding complex issues, such as the effect of CAVs on transportation infrastructure and its readiness. The expert survey used in this case included demographic, Likert Scale, and open-ended questions that allowed the experts to provide detailed and nuanced responses, which provided a more in-depth understanding of the needs of each program/unit within a public agency for the integration of CAVs.

The potential respondents were identified using a variety of methods, including reaching out to TRB committees with a focus on CAVs, ITE chapters across the nation, academics from various institutions, public agency employees, and industry experts through other channels. This comprehensive approach ensured that a diverse range of perspectives and expertise were represented in the survey. A third-party tool, Qualtrics, was used to develop the survey. It was then disseminated to the above groups, providing them with an opportunity to share their thoughts and insights on this important issue.

Despite the medium sample size, the response to the survey was encouraging, with a total of 63 completed and incompleted responses obtained. The participants represented a diverse range of perspectives and expertise, from academics to industry professionals to public agency employees. Their responses provided valuable insights and perspectives on the impact, readiness of public agency program/units, and training needed to accommodate CAVs. Though the sample size may not be representative of the entire population, the data collected will still be useful in informing policy and decision-making in the transportation industry, contributing to shaping the future of transportation in a positive manner.

3.6 Survey Results

In this section, we will present the results of the survey we conducted to get the opinions of various transportation professionals regarding the preparedness of public agencies to accommodate connected and/or autonomous vehicles. In total 63 respondents participated in the survey. Through a series of illustrations, the demographic information of the surveyors and the descriptive statistics of the survey results concerning different aspects of connected and/or autonomous vehicles and public agency units will be presented. Following that, we will conduct a series of hypothesis tests to compare the opinions of the respondents for each question.

3.6.1 Demographics This section presents the demographic information (work location, affiliated organization type, and years of experience relevant to CAVs) of the respondents. Table 7 shows the percentage of respondents for each organization type. Most of them are affiliated with academic institutions. Also, a noticeable fraction of the respondents is associated with consultancy firms and public agencies. Note that about 13% of the respondents are currently associated with multiple organizations. The presence of personnel from different organizations in this survey is clear from this table.

Table 7. *Demographics of the respondents*

Organization Type	% of Respondents
Academia	49.2%
Consultant	20.6%
Public Agency	15.9%
Other	1.6%
Multiple Orgs	12.7%

Figure 17 shows the work location of the survey respondents. It shows that the respondents are from many states of the US as well as from abroad. The number of respondents from North Carolina, California, Florida, and Pennsylvania is noticeable. However, we could not get many participants from the north- and mid-west regions of the US.

Figure 18 shows the distribution of CAV-related work experience of the respondents. More than 80% of the respondents had two or more years of relevant work experience. The majority of the respondents had five or more years of experience.

3.6.2 Descriptive Statistics This section shows the survey results, focusing on the distribution of responses for each question. The following subsections present the descriptive statistics of the result for each category of question(s).

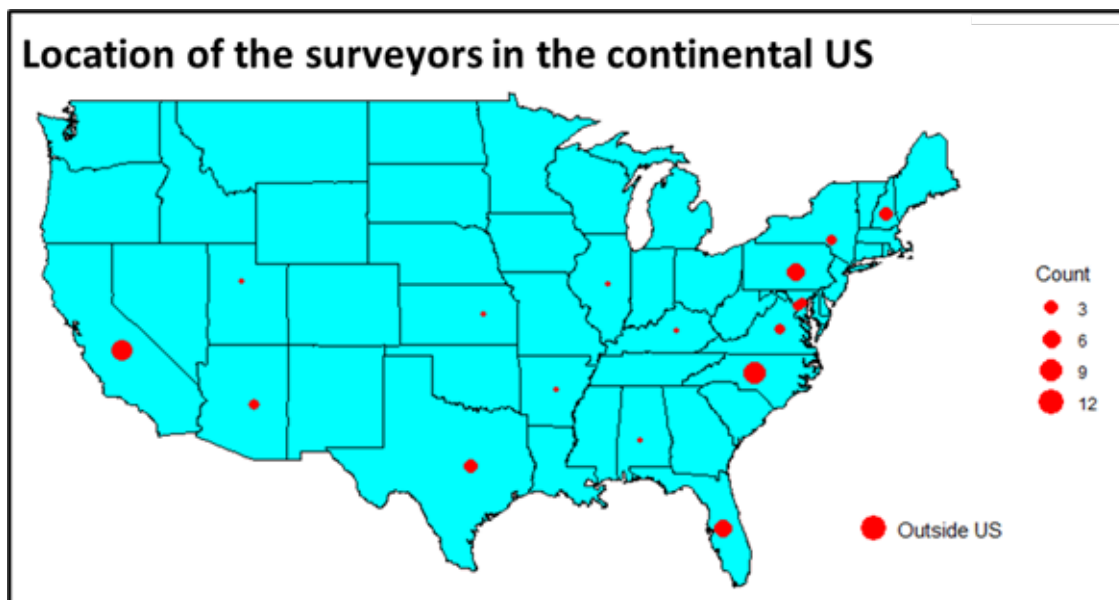


Figure 17. *Location of the respondents in the continental US*

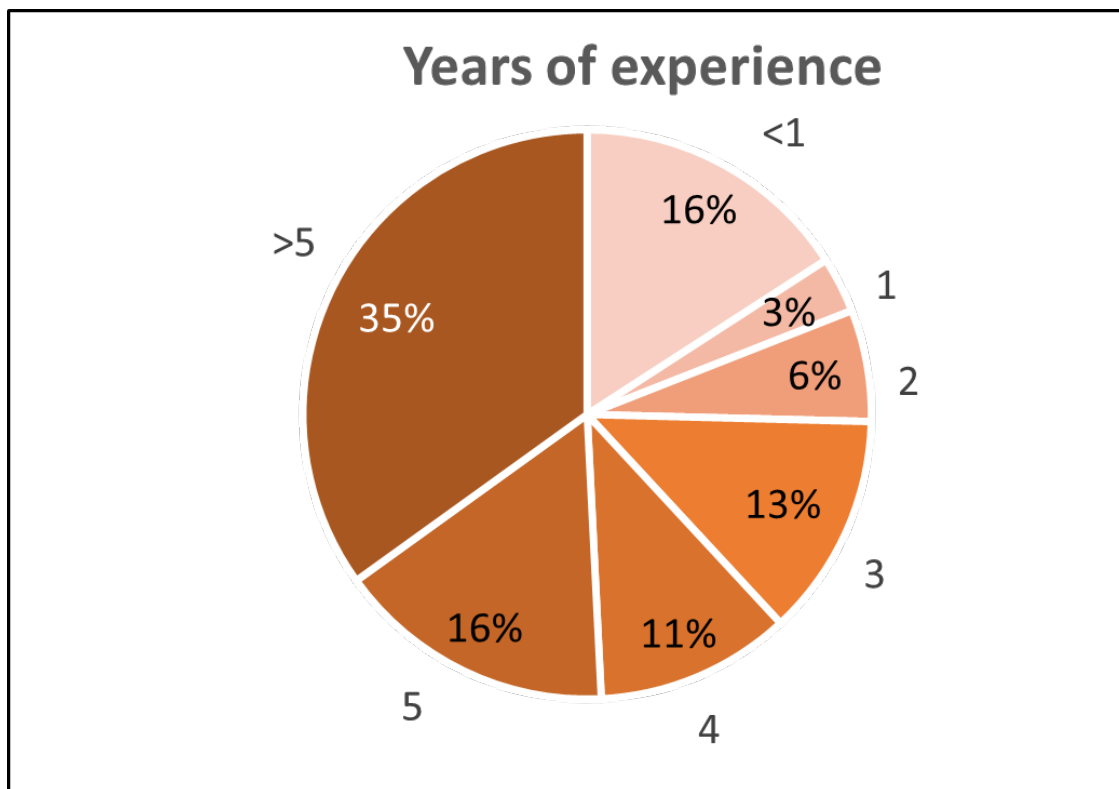


Figure 18. *Years of experience of the respondents in the field of CAVs*

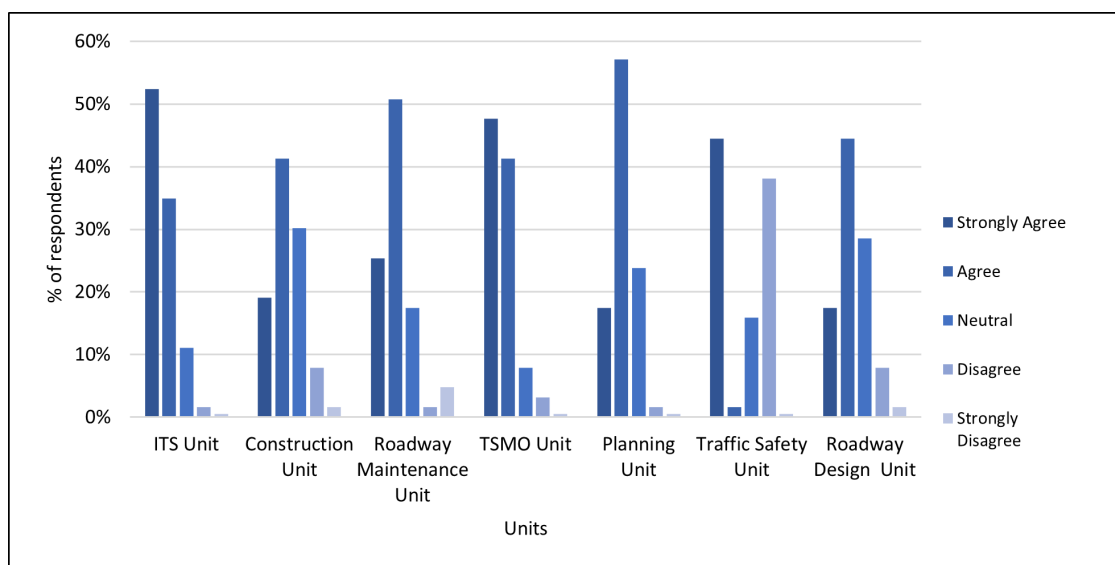


Figure 19. Distribution of responses concerning the impact of connected vehicles

3.6.2.1 CAV Impacts on Various Units of a Public Agency: There are two questions under this category. Their aim was to gauge the impacts of CV, AV, and CAV on various units of a public agency.

- Q 1: How strongly do you agree/disagree with the following statement for each public agency unit listed below?
““(see units below)”” would be heavily impacted if the majority of vehicles were Connected.”

See the survey results in Figure 19.

Key points:

- Most respondents either strongly agreed or agreed with the statement regarding all the public agency units
- For construction, planning, and roadway design units, a significant (24% or more) percentage gave a neutral response
- Less than 10% disagreed or strongly disagreed
 - * Exception: traffic safety unit for which 39% disagreed
- Q 2: “How strongly do you agree/disagree with the following statement for each public agency unit listed below?
““(see units below)”” would be heavily impacted if the majority of vehicles were Autonomous.”

See the survey results in Figure 20.

Key Points:

- Results are very similar to that of the same question regarding Connected vehicles
 - * Most surveyors either strongly agreed or agreed with the statement concerning all the public agency units
 - * A significant percentage of neutral responses is seen for the construction, roadway maintenance, planning, and roadway design units)
 - * Less than 5% disagreed or strongly disagreed

3.6.2.2 Public Agencies’ Readiness to Accommodate CAVs: This question aimed to gauge the public agency unit’s awareness and capability to accommodate CV, AV, and CAV.

- How strongly do you agree/disagree with the following statement for each public agency unit listed below?
“The existing infrastructure or policy and procedure of “(see units below)”” is suitable to accommodate connected and/or autonomous vehicles.”

See the survey results in Figure 21.

Key points:

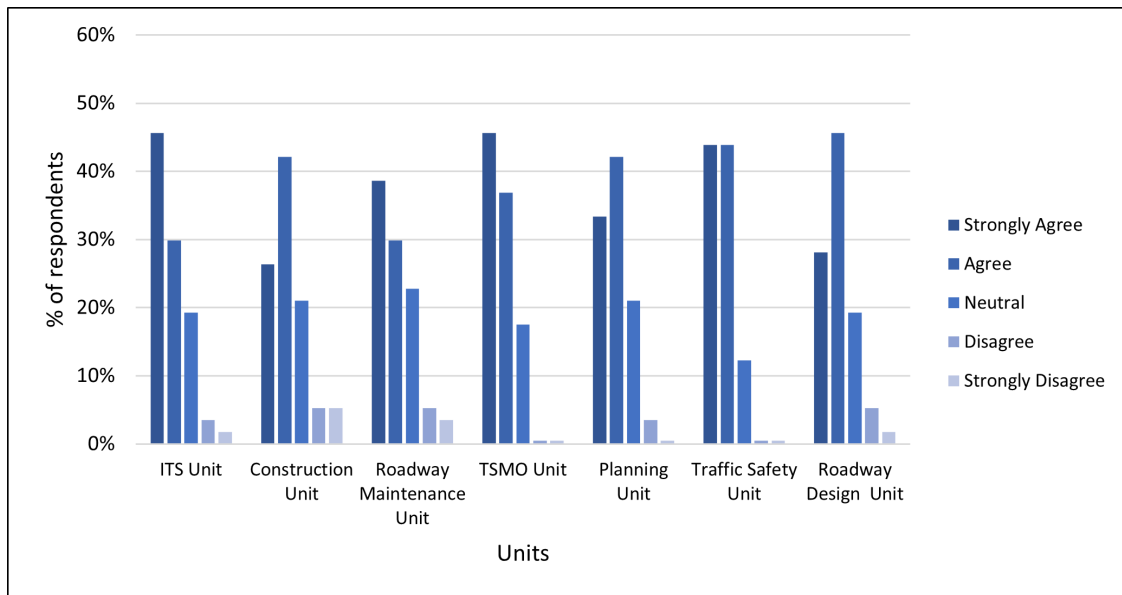


Figure 20. Distribution of responses concerning the impact of autonomous vehicles

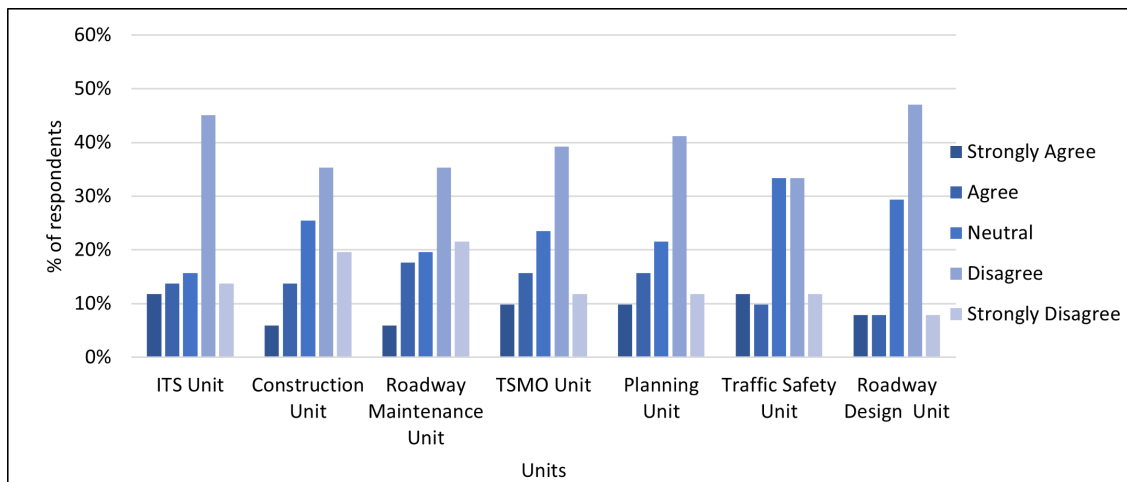


Figure 21. Distribution of responses concerning the status quo of units to accommodate CAVs

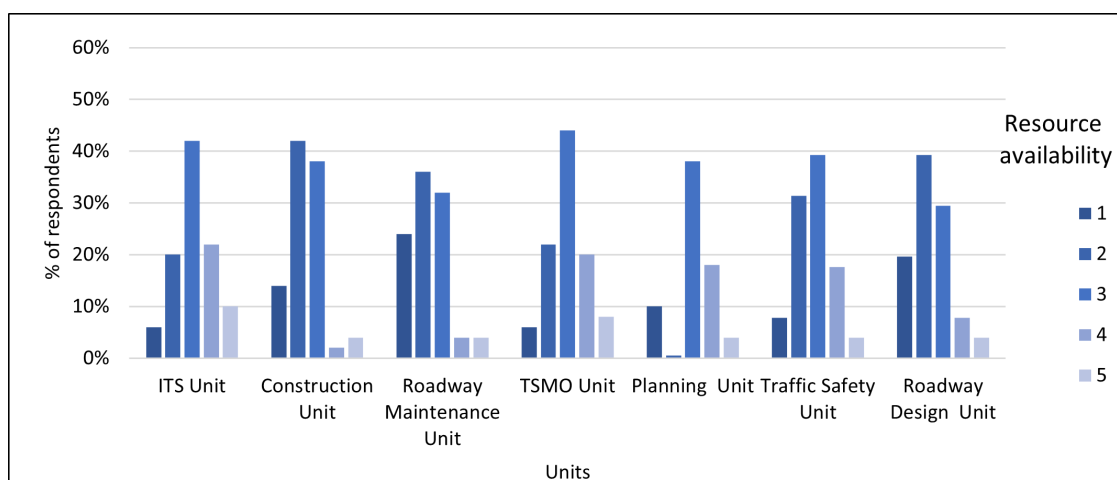


Figure 22. : Distribution of responses concerning the resource availability in preparation for the accommodation of CV, AV, CAV

- Majority (32% or more) agreed with the statement
 - * Exception: for traffic safety unit, the same number of people agreed and gave a neutral response
- About the same number of respondents strongly agreed or strongly disagreed, but their numbers are very few
 - * Exception: When answered for the construction unit, 19% strongly disagreed

3.6.2.3 Public Agencies' Strategic Planning for CAVs: This question aimed to gauge the resource availability in preparation for the accommodation of CV, AV, CAV by public agencies. The respondents were asked to answer the following question on a scale of 1 to 5 (1 being very poor and 5 being very well) for each public agency unit listed below.⁸

- “How well do currently available publications and resources help ‘‘(see units below)’’ to plan for and accommodate connected and/or autonomous vehicles?”

See the survey results in Figure 22.

Table 8. Average scores on resource availability

...(Unit Name)...	Average score
ITS	3.1
Construction	2.4
Roadway maintenance	2.3
TSMO	3.0
Planning	2.8
Traffic safety	2.8
Roadway design	2.4

Key points:

- Majority (36% or more) gave a neutral answer; hence, the average is approximately 3 across all units.
- Very few respondents responded very poor or very well

3.6.2.4 Public Agencies' Training Needs to Accommodate CAVs: This question aimed to gauge training needs for different units of the public agency to prepare for CV, AV, and CAV.

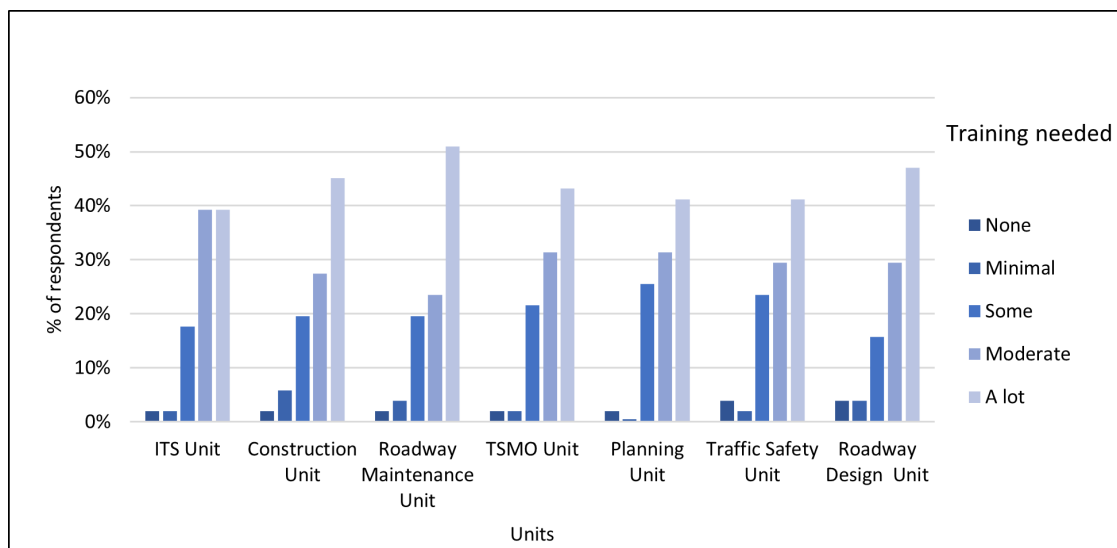


Figure 23. Distribution of responses concerning the training needs in preparation for the accommodation of CV, AV, CAV

- “How much training would ‘‘(see units below)’’ of your state require to accommodate AV and/or CV?”

See the survey results in Figure 23.

Key points:

- Majority (39% or more) responded that a lot of training would be needed. Also, a significant percentage said that a moderate training is needed
- 15-25% respondents said that some training is needed

3.6.3 Summary of Descriptive Statistics: The descriptive statistics of the survey results show that the majority of the respondents agreed that all the units would be heavily impacted if most vehicles were connected or autonomous. Most of them indicated that the existing infrastructure or policy and procedure concerning all the units is still not sufficient to accommodate connected and/or autonomous vehicles. Likewise, many indicated that all the units would need a lot of training to accommodate connected and/or autonomous vehicles. Contrary to these responses, many respondents gave a neutral score on the resource availability to accommodate connected and/or autonomous vehicles. All conclusions (i.e., accept or reject a hypothesis) are drawn based on a significance level of 0.05

3.6.4 Opinion Comparison: Hypothesis Tests: In this section, we will present the results of the statistical analyses we conducted based on the opinions collected from various transportation professionals regarding the preparedness of public agencies to accommodate connected and/or autonomous vehicles. Hypothesis Testing with the Mann-Whitney U-test was conducted to verify whether the mean of the responses is statistically higher or lower than the score of 4 on a Likert scale. The score associated to each answer to the questions are explained in subsequent sections.

3.6.4.1 CAV Impacts on Public Agencies: This hypothesis testing aimed at gauging the impacts of CVs, AVs, and CAVs on various units of a public agency. A total of 63 valid responses were received for the first question. Figure 20 showed the responses earlier. We assigned a score ranging for 1 to 5 for responses from “Strongly Disagree” to “Strongly Agree” (i.e., an “Agree” response has a score = 4) for Q.1 and Q.2. The null and alternative hypotheses are described as follows:

Null Hypothesis (H0): The mean score of the responses is less than or equal to 3.

Alternative Hypothesis (H1): The mean score of the responses is greater than 3. For better readability, Q.1 and Q.2 are repeated below:

1. How strongly do you agree/disagree with the statement for each public agency unit: “...(unit name)... would be heavily impacted if the majority of vehicles were Connected.”
2. How strongly do you agree/disagree with the statement: “...(unit name)... would be heavily impacted if the majority of vehicles were Autonomous.”

The descriptive statistics and hypothesis testing results for each public agency unit are listed in Table 9.

Table 9. Hypothesis Testing Results on Unit Impact Caused by Connected Vehicles. Note: STD = standard deviation and N = sample size.

Hypothesis Testing	Public Agency Unit						
	ITS	Construction	Maintenance	TSMO	Planning	Safety	Design
Avg. Score	4.35	3.70	3.91	4.35	3.94	4.19	3.71
STD	0.806	0.944	0.979	0.765	0.693	0.759	0.923
H0	<=4	<=4	<=4	<=4	<=4	<=4	<=4
H1	>4	>4	>4	>4	>4	>4	>4
N	63	63	63	63	63	63	63
z-Value	3.3564	-1.8672	0.0329	3.3979	-0.476	1.8522	-1.7447
p-Value	0.0008	0.0619	0.9737	0.0007	0.6341	0.064	0.081
Conclusion	Reject H0	Do Not Reject H0	Do Not Reject H0	Reject H0	Do Not Reject H0	Do Not Reject H0	Do Not Reject H0

Results show that among the seven public agency units two (ITS and TSMO) units rejected the null hypothesis and it can be inferred that the mean rating of these groups are statistically greater than or equal to 4 (heavy impact due to connectivity). In comparison, the Construction, Maintenance, Planning, Safety, and Design units tend to not be impacted by connected vehicles as they fail to reject the null hypothesis at the 0.05 significance level.

For the second question, a total of 59 valid responses were received. The descriptive statistics and hypothesis testing results for each public agency unit are listed in Table 10.

Results show that among the seven public agency units two (TSMO and Safety) units rejected the null hypothesis and it can be inferred that the mean rating of these groups are statistically greater than or equal to 4 (heavy impact due to autonomy). In comparison, the ITS, Construction, Maintenance, Planning, and Design units tend to not be impacted by autonomous vehicles as they fail to reject the null hypothesis at the 0.05 significance level.

Table 10. Hypothesis Testing Results on Unit Impact Caused by Autonomous Vehicles

Hypothesis Testing	Public Agency Unit						
	ITS	Construction	Maintenance	TSMO	Planning	Safety	Design
Avg. Score	4.14	3.80	3.95	4.27	4.05	4.31	3.93
STD	0.973	1.063	1.073	0.762	0.839	0.701	0.926
H0	<=4	<=4	<=4	<=4	<=4	<=4	<=4
H1	>4	>4	>4	>4	>4	>4	>4
N	59	59	59	59	59	59	59
z-Value	1.726	-0.6007	0.4775	2.4366	0.717	2.7901	0.0547
p-Value	0.0843	0.5481	0.633	0.0148	0.4734	0.0053	0.9564
Conclusion	Do Not Reject H0	Do Not Reject H0	Do Not Reject H0	Reject H0	Do Not Reject H0	Reject H0	Do Not Reject H0

3.6.4.2 Public Agencies' Readiness to Accommodate CAVs: This hypothesis testing aimed at gauging public agency unit's awareness and capability to accommodate CVs, AVs, and CAVs. The same scoring system and null and alternate hypothesis as to Q.1 and Q.2 are applied here. For better readability, the associated question is repeated below.

- How strongly do you agree/disagree with the statement: "The existing infrastructure or policy and procedure of ...unit name... is suitable to accommodate connected and/or autonomous vehicles."

53 valid responses were obtained in relation to this hypothesis testing question. The results of the analysis (see 11) indicate that none of the seven units surveyed have the infrastructure or policies and procedures necessary for accommodating CAVs, as the mean scores for each unit were statistically found to be less than 4.

Table 11. Hypothesis Testing Results on Unit Readiness to CAVs

Hypothesis Testing	Public Agency Unit						
	ITS	Construction	Maintenance	TSMO	Planning	Safety	Design
Avg. Score	2.66	2.53	2.53	2.74	2.72	2.77	2.62
STD	1.208	1.12	1.17	1.15	1.15	1.14	1.00
H0	>=4	>=4	>=4	>=4	>=4	>=4	>=4
H1	<4	<4	<4	<4	<4	<4	<4
N	53	53	53	53	53	53	53
z-Value	-5.8983	-6.7663	-6.5134	-5.9751	-5.9984	-6.0221	-6.896
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Conclusion	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0

3.6.4.3 Public Agencies' Strategic Planning for CAVs: This section is aimed to conduct a hypothesis testing in order to assess the adequacy of resource availability among public agencies in anticipation of the integration

of CVs, AVs, and CAVs into the transportation system. The same scoring system and null and alternate hypothesis as to the previous questions are applied here. For better readability, the associated question is repeated below

- How strongly do you agree/disagree with the statement: “How well do currently available publications and resources help ...unit name... to plan for and accommodate connected and/or autonomous vehicles?”

A total of 53 valid responses were received for this question that helped the team gain insight into the perceived level of resource availability among public agencies in the context CAVs. Results of the analysis, as presented in Table 12, indicate that none of the seven public agency units surveyed possessed the resources deemed necessary for the adequate preparation for CAVs integration. These findings suggest a potential deficiency in the availability and accessibility of relevant publications and resources for public agencies seeking to accommodate the integration of CAVs. Furthermore research is required in order to identify potential avenues for improvement and to make recommendations for addressing the identified deficiency in resource availability.

Table 12. Hypothesis Testing Results on Resource Availability to Accommodate CAVs

Hypothesis Testing	Public Agency Unit						
	ITS	Construction	Maintenance	TSMO	Planning	Safety	Design
Avg. Score	3.10	2.42	2.31	3.02	2.77	2.79	2.40
STD	1.01	0.89	1.00	0.98	0.98	0.95	1.01
H0	>=4	>=4	>=4	>=4	>=4	>=4	>=4
H1	<4	<4	<4	<4	<4	<4	<4
N	52	52	52	52	52	53	53
z-Value	-5.2193	-7.888	-7.7683	-5.7053	-6.596	-6.655	-7.5331
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Conclusion	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0

3.6.4.4 Public Agencies’ Training Needs to Accommodate CAVs: This section aims to conduct a hypothesis testing to assess the perceived training needs among different units of public agency in anticipation of the integration of CAVs into the transportation system. 53 valid responses were obtained with regard to the question. For better readability, the question is repeated below.

- “How much training would ...unit name... of your state requires to accommodate AV and/or CV?”

The score ranges from 1 to 5 in the following sequence of responses: “None”, “Minimal”, “Some”, “Moderate”, “A lot”. The null and alternative hypothesis statements remain the same as in the previous questions.

The results of the analysis, as presented in Table 13, indicate that none of the seven public agency units surveyed possessed the level of training deemed necessary for the adequate preparation for CAVs integration. These findings suggest a potential deficiency in the availability and accessibility of relevant training for public agencies seeking to accommodate the integration of CAVs. Furthermore, a critical and analytical examination of the results is required in order to identify potential areas for improvement and to make recommendations for addressing the identified deficiency in training availability.

Table 13. Hypothesis Testing Results on Trainings Needed to Accommodate CAVs

Hypothesis Testing	Public Agency Unit						
	ITS	Construction	Maintenance	TSMO	Planning	Safety	Design
Avg. Score	1.92	1.96	1.87	1.92	1.94	2.02	1.92
STD	0.92	1.04	1.02	0.96	0.93	1.05	1.07
H0	>=4	>=4	>=4	>=4	>=4	>=4	>=4
H1	<4	<4	<4	<4	<4	<4	<4
N	53	53	53	53	53	53	53
z-Value	-8.4599	-8.1262	-8.2979	-8.4175	-8.5323	-8.0673	-8.0039
p-Value	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000
Conclusion	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0	Reject H0

3.6.4.5 Summary: The statistical analysis of the survey results show that Connected Vehicles tend to have a more significant impact on the ITS and TSMO units than the Construction, Maintenance, Planning, Safety, and Design units. In comparison, the impacts of Autonomous Vehicles are mostly focused on the TSMO and Safety units as these two units inferred that vehicle autonomy will bring a heavy impact to their units. In terms of public agencies’ infrastructure, policy, and planning readiness to accommodate CAVs, none of these units deemed they are well prepared for the era of CAVs, and all of them agreed that they need more trainings to help prepare public agencies accommodate CAVs.

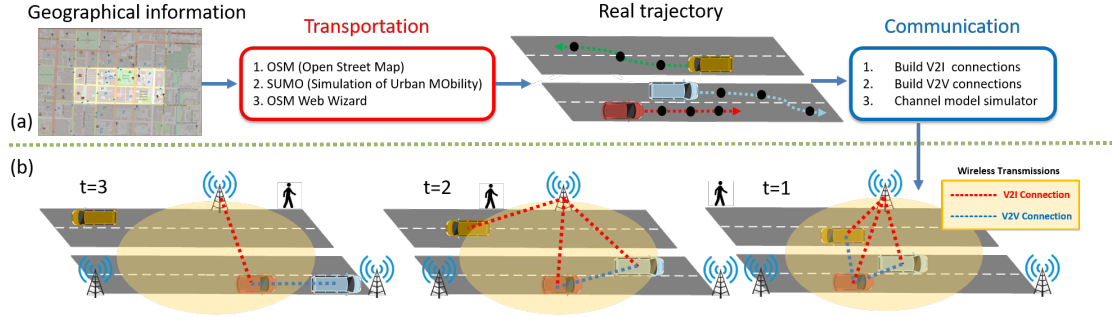


Figure 24. The Illustration of the proposed vehicular communication platform. In the proposed platform, transportation module and communication module are integrated to generate realistic data for verification of vehicular communication algorithms. To be more specific, when a geographical information is imported, transportation module will create realistic traffic on it, then wireless communications will be simulated. As a result, the proposed platform can be used to assess the achieved performance of various vehicular communication algorithms in real scenarios.

3.7 Task 3: Establish Low-Latency Edge Computing Infrastructure Recommendations for North Carolina

With the promising connectivity provided by next-generation communication systems, such as 5G and 6G, several novel applications can be developed in full flourish. Among those applications, intelligent transportation system (ITS) and autonomous vehicles are anticipated to bring new experiences with enhanced efficiency and safety to road users in the near future [178]. In macroscopic scale, with the support of ITS algorithms, the data collected from road users can be used to perform traffic flow prediction, optimal path planning, traffic light control, and so on, leading to the improved transportation efficiency. In microscopic scale, via exchanging information with surrounding vehicles and infrastructures, autonomous vehicles can be employed to assist drivers to mitigate fatigue and increase safety during driving. However, an efficient and robust vehicular communication system with low-complexity should act as a strong backbone to offer the needed infrastructure connectivity of ITS and autonomous vehicles [182]. Notably, we notice that conventional communication protocol-based vehicular networking can only support the latency in the range of 20-100 ms for the following reasons. First, data transmissions rely on initial control signaling storms, which employ closed-loop physical-layer (PHY) protocols, like three-way handshaking, with thousands of control messages for power control or channel estimation in a single PHY link. Second, cumbersome and reactive protocol stacks and higher-layer optimization (i.e., routing and scheduling in networking) take a significant amount of time in computation and information gathering. Third, the high mobility of CAVs incurs tremendous overhead and complexity of protocols, which in turn causes considerable latency for reliable communications. Forth, cloud computation using remote data centers for heavy-weight computation can address the rapid growth of mobile applications and their diverse quality-of-service (QoS) requirements, but at the price of seconds or even larger order in end-to-end latency. Finally, cloud-based models require vehicular data to be transmitted to and stored in data centers, increasing chances of information leakage or loss and longer than expected latency which could even result in fatal accidents. Obviously, current infrastructure cannot satisfy the need for those novel applications by achieving required low-latency requirements since that solely coordination process will cost up to 100 ms to those time-sensitive applications.

As one of 5G and beyond envisioned services, ultra-reliable and low-latency communications (URLLC) aim to provide secure data transmissions from one end to another with ultra-high reliability and deadline-based low latency [2]. Current 3GPP standards for URLLC require 1 ms hard latency over the air interface and 99.999 % system reliability, meeting the needs of autonomous vehicles for performing cooperation and safety functions. Since August 2018, normative works of new radio (NR) vehicle-to-everything (V2X) and enhanced URLLC have been launched in 3GPP Rel-16 [3]. By December 2019, the 3GPP RAN Plenary meeting approved 24 new projects for 3GPP Rel-17 with one primary focus of bringing sidelink capabilities from automotive to smartphones and public safety. Meanwhile, IEEE 802.11p, the basis for dedicated short-range radio communication (DSRC), establishes wireless access in vehicular environments (WAVE) [4] and supports communications among vehicles to enable intelligent transportation services. This technology dedicated for connected vehicles helps exciting SAE Level 3 (conditional automation) trail and soon deployment and targets Level 4/5 (high/full automation) development for self-driving vehicles. However, technological efforts to support mission-critical URLLC requirements are still in an early research stage with no concrete solutions yet. To tackle those demands, in this project, we propose and implement a next-generation edge

computing infrastructure to support low-latency vehicular applications for North Carolina road users. Note that with this realization, the aforementioned exhaustive protocols can be skipped and only needed functionalities should be implemented to provide low-latency communication capabilities. Moreover, with this platform, deep learning vehicular algorithms can be developed easily to further reduce latency of the whole communication system to achieve our promise. In our implementations, as shown in Fig. 24, the proposed platform integrates both transportation and communication modules for the verification of various wireless communication and networking algorithms. Specifically, several open source software, including Simulation of Urban MObility (SUMO), openStreetMap (OSM), and OSM Web Wizard [192], are combined in the transportation module. By doing so, in our transportation module, customized geographic information can be imported as a region of interest first, then realistic trajectories of each vehicle will be created on the region of interest based on adjustable parameters. Given those realistic trajectories, in our communication module, vehicle-to-vehicle (V2V) and vehicle-to-infrastructure (V2I) connections, which is simulated based on latest specifications and papers, are created occasionally to simulate vehicular communication environment. Moreover, we offer sub6GHz and Terahertz (THz) wireless communications for users to choose from now. Different from existing simulation platforms, the trajectories generated from our transportation module will be affected by traffic light and the actions of surrounding vehicles, offering realistic and critical patterns. At the same time, given a interested scenario, the proposed platform can be used to generate huge amount of data quickly, stimulating the development of DL-based vehicular communication algorithms. To validate the proposed platform, we develop a DL-based spectrum management algorithm for sub6GHz vehicular communications. Moreover, the ability of the proposed algorithm to adopt different communication scenarios is also investigated in detail. To explain, spectrum management is an indispensable component to realize efficient vehicular communications. By employing spectrum sensing algorithms in vehicular communications, underutilized spectrum can be reused and consequently leads to a better overall spectrum efficiency [250]. Also, an effective spectrum sensing algorithm can be used as a preceding algorithm to perform critical radio resources allocations in vehicular communications. When it comes to heterogeneous communication systems or military usage [197], spectrum management also shows its importance in terms of provided efficiency improvement. Therefore, we implement critical spectrum sensing algorithms in our platform for further verification. We summarize the major contributions of this work as follows:

- A vehicular communication verification platform is proposed to demonstrate vehicular communication algorithms and assess their performance in real scenarios. To the best of our knowledge, this work is the first to provide an integrated vehicular platform with real traffic simulator and next generation communication systems following specifications and standards. Specifically, realistic traffic in customized region of interest can be created by the transportation module. Then communication connections will be conducted via either sub6GHz or THz bands by the communication module. The proposed platform can be used to demonstrate existing vehicular communication algorithms, especially DL-based algorithm to satisfy the need of hung amount of data with high quality.
- To demonstrate the developed platform, we develop DL-based spectrum management sub6GHz solution based on our previous work [176]. Note all the communication system settings are following latest standard and specifications to better serve current vehicular communications. The comparison of the proposed DL-based and existing generative adversarial network (GAN)-based algorithms is also conducted in different bands. Simulation results reveal that our spectrum management algorithm can offer excellent performance regardless the operation band, showing the practicality of our spectrum management algorithm.
- With similar concept, we further develop three DL-based algorithms for vehicular communications and provide details in Appendix. C, Appendix. D, and Appendix. E for interested readers. Note that all different algorithms can be developed and demonstrated using the proposed SD-VEC platform to accelerate the development of vehicular communication systems.

3.7.1 Signal and Communication Setups: Considering a vehicular communication scenario, followed by cellular-V2X (C-V2X) structure with operation frequency band $[W_1, W_2]$ (Hz), a base station (BS) serves several user equipments (UEs) in its cell coverage. To increase spectrum efficiency by performing spectrum management, each transmission time-slot will be divided into two phases: sensing phase and data transmission phase. In sensing phases, an UE, which wishes to create new connection using spectrum holes in the radio environment, will perform spectrum sensing to detect existing connections and seek for idle bands first, then the desired connection can be built in the following data transmission phase. Suppose there are I connections existing in the time-slot, the received signal $\mathbf{x}_c(t)$

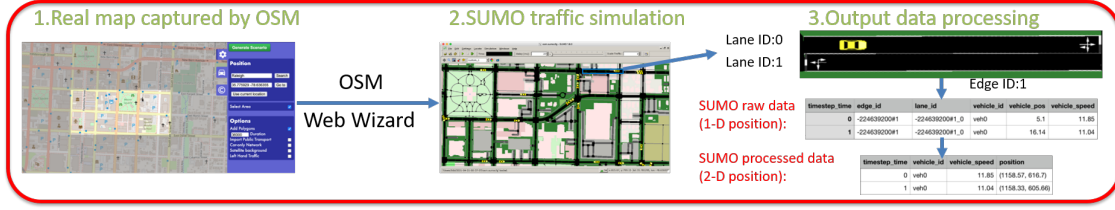


Figure 25. The detailed process of the transportation module: Using the transportation module, realistic traffic will be created in region of interest and the trajectories of vehicles will be recorded for further use.

at the UE side can be modeled as

$$\mathbf{r}_c(t) = \mathbf{x}_c(t) + \mathbf{w}(t) = \sum_{n=1}^I \mathbf{h}_n(t) * \mathbf{s}_n(t) + \mathbf{w}(t), \quad (3.1)$$

where $\mathbf{s}_n(t)$ and $\mathbf{h}_n(t)$ are the transmitted signal and corresponding channel effect of existing transmissions and $\mathbf{w}(t)$ is the noise in receiver side. In a given sensing phase, by using an ADC with Nyquist sampling rate f_s , a perfect discrete time sequence $\mathbf{r}[n] = \mathbf{x}[n] + \mathbf{w}[n] = \mathbf{x}_c(\frac{n}{f_s}) + \mathbf{w}(\frac{n}{f_s})$, $n = 0, 1, \dots, N_s - 1$ can be obtained as $\mathbf{r} \in \mathbb{C}^{N_s \times 1}$. Also, the corresponding discrete Fourier transformation (DFT) spectrum can be obtained by performing $\mathbf{R} = \mathbf{F}\mathbf{r}$, where $\mathbf{F}$ is the DFT basis matrix. However, getting DFT spectrum in this way is costly and impractical. To tackle this drawback, spectrum reconstruction problem will be introduced and formulated.

3.7.2 Problem Formulation: Sub-Nyquist sampling and spectrum reconstruction based on undersampled measurements can be introduced to avoid the exhausted sampling process. To explain mathematically, a sub-Nyquist sampling process can be expressed as

$$\mathbf{y} = \Phi \mathbf{F} \mathbf{r}, \quad (3.2)$$

where $\Phi_{M \times N_s}$ is the sensing matrix, which satisfies $M < N_s$ to perform compression. Our goal in this paper is to design a way to reconstruct the the desired signal $\mathbf{x} \in \mathbb{C}^{N_s \times 1}$ or corresponding clean DFT spectrum $\mathbf{X} = \mathbf{F}\mathbf{x}$ from the noisy and undersampled measurements $\mathbf{y} \in \mathbb{C}^{M \times 1}$. Traditional compressed sensing algorithms can be used to perform reconstruction by solving the optimization problem:

$$\begin{aligned} & \underset{\mathbf{x}}{\text{minimize}} \quad \|\mathbf{x}\|_1 \\ & \text{subject to} \quad \|\mathbf{y} - \Phi \mathbf{F} \mathbf{x}\|_2 \leq \epsilon, \end{aligned} \quad (3.3)$$

where ϵ is the distortion threshold. However, the computational efficiency and execution time can be further improved. To explain, existing spectrum reconstruction algorithms only focus on the design of reconstruction process and ignore the design of compression process, limiting the achieved efficiency. As an alternative, we aim to design a joint compression and reconstruction algorithm to improve the overall efficiency. Hence, instead of solving Eq. (3), the interested joint optimization problem can be expressed as:

$$\underset{f, \Phi}{\text{minimize}} \quad \|\mathbf{X} - f(\Phi \mathbf{F} \mathbf{r})\|_2, \quad (3.4)$$

where f is the reconstruction function.

3.7.3 The Development of DL-based Spectrum Reconstruction: To solve the optimization problem in Eq. (4), we develop a DL-based algorithm to perform efficient compression and reconstruction. To explain, designing and evaluating a sensing matrix in the compression process via optimization-based algorithms is not travail, turning out that existing algorithms only focus on solving Eq. (3) instead of solving Eq. (4). In the proposed algorithm, benefiting from the end-to-end learning nature of DL-based algorithm, backpropagation algorithm is used to improve the compression and reconstruction process simultaneously via gradient decent mechanism in each epoch, achieving effective joint optimization. As a result of the joint optimization, undersampled measurements with more critical information compared to existing algorithms can be obtained, leading to better efficiency and consequent better reconstruction results.

3.7.3.1 Deep Learning Model Architecture: We create three consecutive modules (namely compression, coarse reconstruction, and fine reconstruction modules) in our DL model for efficient spectrum reconstruction. The compression module is a specially-designed one-layer convolutional neural network (CNN) with M filters to produce undersampled measurements by making the trainable weights in the compression module act as the content of sensing matrix, being expressed as:

$$\mathbf{z}_{DL} = \Phi_{DL}\mathbf{Fr}, \quad (3.5)$$

where $\mathbf{Fr} \in \mathbb{C}^{N_s}$ is the original spectrum, $\Phi_{DL} \in \mathbb{C}^{M \times N_s}$ is the sensing matrix designed by the compression module, and $\mathbf{z}_{DL} \in \mathbb{C}^M$ is the obtained undersampled measurements. To be more specific, the input of the compression module $\mathbf{Fr}$ is presented as a real vector with the size of $N_s \times 2$. After the operation of the *compression module*, the output $\mathbf{z}_{DL}$ is a real vector with the size of $M \times 2$, standing for the real part and the imaginary part of the undersampled measurements. Note that there is no activation function in this CNN layer to ensure the whole compression module as a linear operation. After training, the trainable weights in each filter can be represented as a pseudo-random (PN) sequence [205]. Then received signals will be mixed with M PN sequences and pass through a low-pass filter to get the undersampled measurements $\mathbf{z}_{DL}$ in real scenarios. Once we get the undersampled measurements $\mathbf{z}_{DL}$, coarse reconstruction and fine reconstruction module will be employed to perform spectrum reconstruction. The coarse reconstruction is another CNN layer, which has N_s filters with the size of $M \times 2$, to generate initial reconstruction. Different from the compression module, batch normalization (BN) and PRelu are employed in this CNN layer to offer nonlinearity. Then the fine reconstruction module, which is developed based on ResNet-structure and has six residual blocks, will be employed to finish final reconstruction. In each residual block, three CNN layers with number of filters 64, 32, and 2, respectively, are built to refine the initial spectrum reconstruction. Behind each layer, we also employ BN and PRelu in the initial reconstruction module to complete the fine-scale reconstruction.

3.7.3.2 Loss Functions: To leverage the end-to-end training mechanism for solving interested optimization Eq. (4) efficiently, Eq. (4) is employed as the loss function of the aforementioned model directly. Let Θ_{CR} stands for the trainable weight in the coarse reconstruction module and Θ_{FR} represent the trainable weight in the fine reconstruction module and $f(x; \Theta_{CR}, \Theta_{FR})$ is the nonlinear transformation with Θ_{CR} and Θ_{FR} , the loss function can be expressed as

$$Loss = \|\mathbf{Fs} - f(\Phi_{DL}\mathbf{Fr}; \Theta_{CR}, \Theta_{FR})\|^2. \quad (3.6)$$

During each epoch, Φ_{DL} , Θ_{CR} , and Θ_{FR} will be updated jointly to minimize the training loss until convergence, generating optimal sensing matrix and trainable weights in each module. As for the training specifics, the Adam optimizer with initial learning rate 0.0005 is employed to minimize the loss function. The number of epochs is set as 20 and the mini-batch mechanism is employed with batch size as 128 to facilitate fast convergence.

3.7.4 A New C-V2X Platform and Numerical Results: To evaluate the performance of vehicular algorithms in real scenarios, as shown in Fig. 24, we create a platform integrating real transportation module and spec-defined communication module to obtain simulation results.

3.7.4.1 Transportation module: In order to obtain realistic traffic data, we introduce SUMO [192] as the transportation module of the proposed platform. To explain, SUMO is an open source platform that can create microscopic realistic traffic data. Moreover, with the OSM combination, we can import the geographic information from real map to evaluate the achieved performance of vehicular communication algorithms in any region of interest of real locations. As shown in Fig. 25, given a fixed location, in our transportation module, several parameters can be adjusted to simulate the transportation behavior during different time or events. In this paper, a two direction street with four lanes in Raleigh Downtown, North Carolina is selected as region of interest to investigate the behavior of vehicular communication algorithms in Urban scenario. The area we selected for simulation is around 600k m^2 and traffic lights are built and used to control the traffic in this area. The time step is set for 1 second and the average seconds of a new vehicle generated on the map is set as 2.5. Furthermore, we adopt vehicles with 5 m length and 1.8 m width to finish the simulations. The maximum speed of each vehicle is set as 55.56 m per second, and minimum gap of two vehicles is 2.5 m . It is noteworthy that the aforementioned parameters can be adjusted flexibly to reflect the traffic in peak hours or non-peak hours or to match any communication specifications or standards. Moreover, different type of vehicles with different size can be simulated by SUMO platform to generate realistic traffic behavior. Based on the aforementioned settings, SUMO raw dump traffic data will be created. Then the original one-dimensional position data will be converted to two-dimensional position data first and be passed to communication module for further processing.

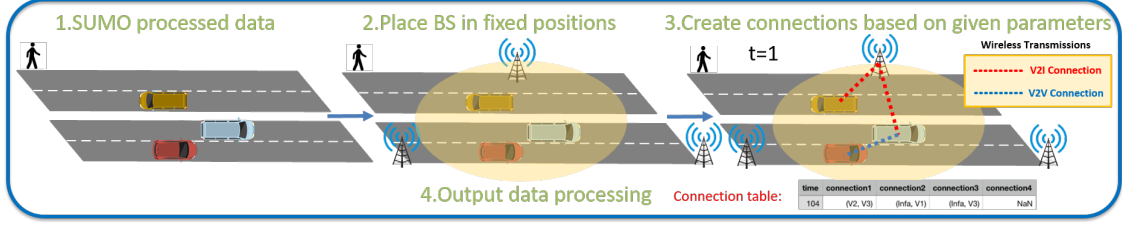


Figure 26. The detailed process of the communication module: In each time step, based on the realistic trajectories data and communication system settings, wireless connections will be created and the detailed information is also provided in our platform.

3.7.4.2 Communication module: After we get the discrete traffic data generated from the transportation module, we follow the latest settings of standards and specifications to construct the communication module. To be more specific, we set one BS on middle of the road. The distance between the V2I connections (i.e., BS and any vehicles) and V2V connections (i.e., any pairs with two vehicles) can be calculated in each time step. In the coverage of the BS or the maximum communication range of V2V connections, we set that for each vehicle there is 0.9 chance that it is communicating with the BS and for each pair of vehicles there is 0.5 chance that they are communicating with each other to create V2V and V2I connections. Next, it is noteworthy that we offer different operation band options with realistic channel behavior to perform simulations in our communication module. Specifically, in Release 17 [112] announced in December 2019, frequency range 1 (sub6GHz) is still considered to support C-V2X communications. We further consider THz band as an option in our platform for next-generation communications. The comparison of achieved performance in those bands can act as a useful reference for system designer to determine the actually band for different applications. We set W_1 and W_2 as $[0, 2GHz]$ according [290] to simulate wideband scenario in sub6GHz band. When it comes to the THz band, we follow our previous paper [176] to set W_1 and W_2 as $[0.1THz, 0.55THz]$. As for the coverage of V2V and V2I connections, we set that as 100m for sub6GHz band and 15m for THz band based on latest papers. In summary, there are 2GHz and 450GHz available bandwidth for the usages of sub6GHz and THz transmission, respectively.

As for the channel effect, we consider frequency and distance-dependent path loss in both bands following the suggestions of 3GPP simulation guideline and latest papers [112]. Specifically, the block slow fading channel with the path loss: $127 + 2 * \log_{10}(f) + 30 * \log_{10}(d)$, where d (km) is the distance and f is the center frequency of each connections, is set for sub6GHz band. As for THz band, we follow the setting in our previous paper [176] to simulate realistic THz channel behavior with the consideration of non-ideal conditions, such as temperature, atmospheric pressure, air density and non-line of sight effect. The whole simulation process of communication module is shown in Fig. 26, in each time step, different number of connections will be created based on the given trajectories and aforementioned communication parameters. Moreover, the detailed information about the transmitter and receiver of each connection is also provided in the proposed platform.

3.7.4.3 Data set generation: By integrating the above two modules, we generate realistic data set for the training of DL-based algorithms. Specifically, different from existing works, which employs simple transportation model to describe the vehicle mobility, the trajectories of each vehicle are affected by adjacent vehicles and traffic lights on road in our simulations, leading to more realistic simulation results. Based on these trajectories, V2V and V2I connections are built occasionally in our communication module. As compared to latest spectrum reconstruction algorithms, which assumes fixed number of existing connections in their simulations, it is noteworthy that the number of valid connections may change in each sample in our simulations, challenging the ability of DL-based reconstruction algorithms but being more similar to real scenarios. When all the communication connections are generated, we assume $N_s = 256$ subcarriers equally spaced within the available bandwidth. We further assume that each existing users chose a random, non-overlapping group of 5 subcarriers to transmit on, with at least 1 subcarriers of guard on either side. Finally, antenna gains from transmitter G_t and receiver G_r are set as 0 dbi for sub6GHz and 50 dbi for THz bands, respectively for fair comparison. Although we consider the single input single output structure for the communication system design of each band, the achieved results should be the same for multiple input multiple output structure as the only difference is the provided array gain in our interested problem. For each operating band, we generate 50000, 10000, and 10000 samples and corresponding labels for training, validation, and testing sets, respectively. Note that all the inputs and labels are normalized as $[1, 0]$ to prevent computational issues of DL-based

Table 14. Comparison of spectrum reconstruction in different bands with SNR = 30 dB and compression rate = 0.125

	GAN		Proposed	
	sub6GHz	THz	sub6GHz	THz
Machine learning performance metrics				
MSE	0.0685	0.0187	0.0026	9.61e-04
Cosine Similarity	0.3370	0.4394	0.9951	0.9908
SSIM	0.3033	0.6289	0.8523	0.9386
Communication performance metrics				
P_d	2.47e-04	0.0622	0.9	0.9449
P_f	0	2.68e-04	2.6e-04	0.0014

algorithms. All the reported results are the average values over the testing set.

3.7.4.4 Performance Metrics: We assess different algorithms from both machine learning and communication perspectives in this paper. As for the machine learning performance metrics, mean-square-error (MSE), cosine similarity, and structure similarity (SSIM) between original spectrum and reconstructed results, are reported in this paper [176]. As for the communication performance metrics, we combine the output of different spectrum reconstruction algorithms with simple energy detection mechanism to perform spectrum sensing. In both original and reconstruction spectrum, a subcarrier will be considered as occupied if the power of it exceeds 0.5. Then detection rate P_d and false alarm rate P_f can be calculated to reflect the spectrum sensing performance, Note that the better trade-off between P_d and P_f implies the better spectrum efficiency and better communication quality as new users can always find spectrum holes to conduct interference-free data transmission.

3.7.4.5 Performance Comparison: Table I reflects the achieved performance of different algorithms in different operating bands with signal-to-noise ratio = 30 dB and compression rate = 0.125. In both sub6GHz and THz bands, the proposed algorithm outperforms GAN-based algorithm in various performance metrics significantly. To be more specific, in terms of machine learning performance metrics, the proposed algorithm can offer excellent reconstruction results, which is very close to the original spectrum. Moreover, the proposed algorithm can strike a good trade-off between detection rate and false alarm rate to aid vehicular communications. On the other hand, the reconstruction quality provided by GAN-based algorithm is unacceptable, failing to reflect the utilizing situations of original spectrum and failing to perform effective spectrum management. Specifically, it is noteworthy that the detection rate of GAN-based algorithm is far less than 90%, which is unsatisfactory for any communication systems. It is also noteworthy that the simulation results reveal that the proposed spectrum reconstruction can be employed in different bands as its data-driven nature can adopt different channel characteristics automatically. Finally, although THz bands can provide abundant bandwidth to support data rate-demanding or low latency applications, we report that the extra power consumption or advanced technologies (i.e., beamforming technique, antenna design) should be used to overcome the higher path loss compared to sub6GHz band.

3.7.5 Conclusion: We propose a vehicular communication verification platform to facilitate the development of DL-based C-V2X communications and realize infrastructure with extremely low latency. A transportation module based on SUMO for realistic transportation data and a communication module based on the latest specifications are integrated to offer practical simulation results. Using the proposed platform, we further develop a DL-based spectrum management algorithm for the sub6GHz band and investigate the adaptability with actual transportation data and different communication settings. Simulation results confirm that the proposed algorithm can be employed in various communication systems to offer impressive results. For future work, we plan to add other 3GPP communication options, such as millimeter wave, and connection types, such as vehicle-to-pedestrian and vehicle-to-network connections. Moreover, we will create computation module to address computation-related issues, including edge computing, on-device learning, and distributed machine learning training in vehicular communications.

3.8 Task 4: Recommend Program Enhancements to Further NC Readiness for CAVs

The integration of connected and autonomous vehicles (CAVs) into our transportation systems presents both opportunities and challenges. Adequate transportation infrastructure is essential for the successful deployment and operation of CAVs. This project investigates 1) current NCDOT Programs that may be impacted by the changes to traditional infrastructure needed to safely deploy CAVs statewide, 2) expand on a low-latency edge computing architecture that can support CAV applications needing extensive computation or timely response, and 3) provide

recommendations to NCDOT to increase statewide readiness for CAVs in both traditional and emerging infrastructure.

An Expert Survey was conducted to identify public agencies' programs that may be impacted by the changes to the traditional infrastructure needed to safely deploy CAVs statewide. The survey contains questions that identify and gauge 1) impacts of CAVs on various units/programs of a public agency, 2) unit/program awareness and capability to accommodate CAVs, 3) resource availability in preparation for accommodation of CAVs, and 4) training needs to prepare for CAVs.

The results of the expert survey reveal that the transportation infrastructure in the public sector is not yet fully prepared to accommodate the integration of connected and autonomous vehicles (CAVs). The survey results indicate that connected vehicles are expected to have a significant impact on most units of the public agency, except for roadway maintenance and planning units. On the other hand, autonomous vehicles are expected to have a significant impact primarily on the Transportation Systems Management and Operations (TSMO) and Traffic Safety units, but not on other units such as ITS, construction, roadway maintenance, planning, and roadway design.

Moreover, the survey results demonstrate a universal consensus among the respondents that the current infrastructure is inadequate to accommodate CAVs for all public agency units. Furthermore, it was identified that there is a shortage of resources and training to assist public agency units in preparing for the integration of CAVs. These findings imply that there is a need for increased investment and resources to ensure the readiness of transportation infrastructure for the integration of CAVs. Additionally, more efforts should be made to provide training and education to public agency units to help them accommodate the integration of CAVs.

Findings of the survey indicate that:

- Connected vehicles will significantly impact most of the units except roadway maintenance and planning units.
- Autonomous vehicles will significantly impact the TSMO and Traffic Safety units, but do not significantly impact the other units (ITS, construction, roadway maintenance, planning, and roadway design)
- A universal consensus emerged from the survey that the existing infrastructure is not able to accommodate CAVs for all the public agency units
- In regard to public agency's strategic planning for CAVs, there is a blanket consensus among the survey respondents that there is not enough resources to help prepare all of the public agency units to accommodate CAVs
- When it comes to the public agency's training needs to accommodate CAVs, the result of the survey indicated that within all units of the public agency there is not enough training to help prepare them for accommodation of CAVs.

Based on the findings of the survey, the recommendations for the North Carolina Department of Transportation (NCDOT) to improve the readiness of transportation infrastructure for the integration of CAVs are i) increase investment and resources to improve the existing infrastructure, ii) develop a comprehensive strategic plan to address the impact of CAVs on the transportation infrastructure and the necessary steps to prepare for their integration, iii) Provide training and education opportunities to staff to help them understand and adapt to the integration of CAVs, iv) be part of and implement Connected Vehicle Pilot projects such as the Multimodal Connected Vehicle Pilot Project lead by NCDOT.

Through the above investigations and findings, as for infrastructure part, we conclude that software-defined infrastructures are essential to realize further NC readiness for CAVs. To explain, with software-defined architecture, the expectation towards next-generation communication systems can be fully fulfilled by intelligently coordinating communication, computation, and sensing capabilities. As a result, sensing functionality can be used to provide environment information for two usages. First, those sensing information can be utilized to enable physics-enhanced communications, considering environment information to provide precise communication operations. Second, with the aid of communication functionality, environment information among several sensors can be aggregated to expand the field of view, providing further security to road users. In the above procedures, computation functionality can be employed to aid both usages by accelerating sensing and communication operations since those operations may involve computationally intensive parts. Note that software-defined infrastructures are essential to realize further NC readiness for CAVs by offering a platform to coordinate communication, computation, and sensing capabilities to enable those procedures. As for connectivity and autonomy part, we also suggest that machine learning techniques are essential to realize further NC readiness for CAVs. To elaborate, machine learning techniques can provide significant

contributions in two scenarios. First, in the considered vehicular scenario, machine learning techniques can be used to realize real-time and autonomous operations to satisfy the limited responding time requirements in such scenario. Second, considering that vehicular scenario is a fast changing and challenging scenario, with appropriate training procedures, machine learning techniques can be used to provide desired outcomes even through the underlying system model is unknown or imprecise. As a result, we also conclude that machine learning techniques are essential to realize further NC readiness for CAVs from the connectivity and autonomy perspective.

The recommendations outlined in this report provide steps to address the infrastructure readiness for CAVs. Investing in transportation infrastructure, developing regulations and standards, encouraging collaboration, implementing smart city technologies, investing in public transportation, and planning for the integration of other emerging technologies are all key steps towards ensuring that our transportation infrastructure is ready for the future. However, it is important to note that the development and deployment of CAVs is a complex and ongoing process. It requires the collaboration of various stakeholders including government agencies, private companies, research institutions, and the public. Therefore, it is crucial to continue monitoring and evaluating the progress of these recommendations and make adjustments as necessary.

In summary, transportation infrastructure readiness for CAVs is a critical component for the successful deployment and operation of these vehicles. By taking a proactive approach and working together, a transportation system that is safe, efficient and ready for the future will emerge.

Chapter 4 : Research Findings under Thrust 3 (Developing and Implementing CAV-UAV Collaboration for Advancing the Transportation Systems)

4.1 Background

With advances in control, sensing and perception, high performance computers, cloud computing, and communication technologies, it is becoming possible to have heterogeneous transportation systems incorporating autonomous ground and air vehicles that communicate with each other and also with smart infrastructure to effectively provide transportation services distributed in time and space. Connected Autonomous Vehicles (CAVs) have the capability to communicate with devices both within and outside the vehicle (including other vehicles and road or network infrastructure) to share and process data in order to improve the safety and performance of individual vehicles and of the overall transportation system. Higher autonomy levels of CAVs along with their connectivity allow for a cooperative control strategy that provides a more flexible and efficient transportation system to serve as an on-demand-mobility solution. Further, cooperative control of CAVs offers a promising solution that increases traffic efficiency and enhances traffic navigation through congested urban environments such as road intersections or unforeseen situations that may arise during travel/transportation. For example, cooperative control of CAVs can enable Cooperative Adaptive Cruise Control (CACC) which is achieved based upon the communication between CAVs. As another example, the traditional signaling at intersections can be replaced by the cooperative control of CAVs with the capability to communicate with each other and the road infrastructure to reduce the possibility of congestion at intersections. Also, CAVs are not limited to ground-based autonomous vehicles: Advanced air traffic management systems using Unmanned Aerial Vehicles (UAVs) such as air taxis can complement ground transportation systems. UAVs can also provide aerial traffic monitoring, traffic guidance, and control for traffic incident and emergency management. Motivated by these challenges and applications, this project will explore the emerging applications of CAVs for enhancing transportation systems.

The goal of this project is to develop and implement cooperative control techniques for CAVs and UAVs and explore their emerging applications by achieving the following objectives:

- **Objective 1:** Developing Cooperative control of heterogeneous CAVs and UAVs for on-demand mobility applications.
- **Objective 2:** Prototyping a testbed of a network of CAVs.
- **Objective 3:** Aerial monitoring using CAVs.

4.2 Task 1: Literature Review

Connected autonomous vehicles (CAVs) promise to provide efficient solutions for increasing transportation demands. Taking the advantage of a high level of connectivity and autonomy, CAVs combine the performance of autonomous vehicles and intelligent transportation services to provide transportation services distributed in time and space, while enhancing transportation systems' safety, reliability, and efficiency. The high level of autonomy enables CAVs to perceive the surrounding environment with multimodal sensors and to make intelligent control decisions by fusing information gathered from different sensors. On the other hand, the connectivity of CAVs enables cooperative functionalities so that a network of vehicles can drive in a coordinated way while communicating with users to optimally manage resources and demands in the transportation system as shown in Fig. 27.

Throughout the last two decades, most CAV development efforts focused on (a) enhancing the autonomy of vehicles by understanding the surrounding environments using multi-modal sensing and safe control operations including path planning, lane-keeping, adaptive cruise control, automated parking, etc., and (b) enabling V2X (vehicle-to-everything) communication including, but not limited to, V2I (vehicle-to-infrastructure), V2N (vehicle-to-network), V2V (vehicle-to-vehicle), V2P (vehicle-to-pedestrian), V2D (vehicle-to-device), V2C (vehicle-to-cloud), and V2G (vehicle-to-grid) using infrastructures like communication base stations, roadside units (RSUs), and software-defined networks (SDNs). With these capabilities, CAVs have the potential to drastically transform the transportation systems and significantly impact the agencies responsible for the planning, design, construction, operation, and maintenance of the roadway infrastructure [98,288]. Numerous studies are conducted to assess the operational and safety benefits of CAVs [29,59]. Broadly speaking, these studies focus on transformative safety, mobility and transportation efficiency, and fuel consumption and energy saving of CAVs. Despite these benefits,

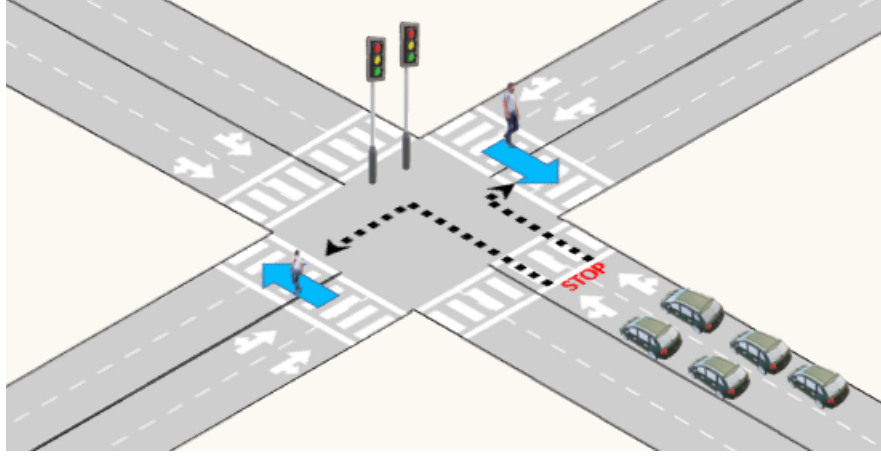


Figure 27. CAVs offer cooperative functionalities to optimally manage resources and demands, and safety in the transportation system.

CAVs also bring their own challenges such as reliability of data communication, cybersecurity protection, regulatory aspects, infrastructure needs, etc.

In this report, under Appendix A, we provide a comprehensive review of the state-of-the-practice of CAV technology and investigate the current CAV tests-beds including their design, automation solutions, communication backbone, and computation needs. Appendix A also summarizes the CAV impacts from a statistical perspective and identifies some of the potential impacts of CAVs on roadway design, traffic control device standardization, and the infrastructure needs to facilitate the worldwide deployment of CAVs. Additionally, we provide general guidance and recommendations on how the infrastructures need to be prepared for the future deployment of CAVs. Further details about this literature on state-of-the-practice for deployment of CAVs is included under Appendix A.

4.3 Task 2: Development of Cooperative Control of Heterogeneous CAVs for On-Demand Mobility

On-demand ridesharing is a promising solution for alleviating urban mobility issues such as traffic congestion, environmental pollution and shortage of parking space which are mainly caused by increased personal mobility [15]. The benefits of ridesharing has motivated transportation service providers like Uber, Lyft and Via to invest huge capitals into ridesharing [285]. The benefits of ridesharing include: the fare per person for a trip is reduced by sharing the cost among passengers; and the service providers can acquire more profit by serving more requests with the same number of available vehicles. It is estimated in [19] that 20% of the current taxi fleet are sufficient to serve 98% of the demand in Manhattan, New York City.

The large scale nature of the ride-sharing problem, combined with the real-time response and profitability requirement forms the core technical challenges. The ridesharing problem involves exploring a very large search space and providing solutions fast enough to enable ridesharing users experience real-time service. The solution space of the ride-sharing problem increases significantly in proportion with the service requests and vehicle capacities, therefore, many proposed algorithms opt for linear programming when considering a small number of fleets [273] or greedy algorithms [303] for large fleets. It should be noted here that, greedy algorithms do not guarantee optimality which affects the original purpose of effectively solving the ride-sharing problem.

In this regard, online batch assignment techniques are proven to be effective in solving large scale high capacity on-demand ridesharing problems. Batch assignment approaches can be categorized into single and multiple batch assignment. In [19, 167], an online multiple batch assignment approach is considered for assigning requests to vehicles, but the algorithms suffer from a high computational complexity. A single batch assignment approach proposed in [285] proved to be efficient, however, they formulated the ridesharing problem as a linear assignment program, therefore, the formulation lacks the ability to handle large scale instances. Also, it mainly optimizes the number of requests served as opposed to other benefits of ridesharing. In our work, an efficient online single batch assignment that can handle large scale high-capacity ridesharing problem is considered.

On the other hand, existing works employing these approaches include allocating of vehicles to requests and routing them to their destinations [19, 167, 293, 303, 347], rebalancing of idle vehicles to high demand regions [321, 333] and prediction of future demands [20, 276, 307]. However, most of these studies give little to no attention to the benefit

that the service provider will obtain in terms of profit. They only focus on improving the quality of service offered to the user. As opposed to most previous work, a vehicle dispatch formulation that optimizes the system's profit was considered in [348]. Nevertheless, it did not take into consideration late arrival compensations. A similar formulation to our work, which also optimizes the system's profit is presented in [168]. They estimated the fare each request in a trip pays in terms of the travel distance. However, fare estimation based on travel distance deteriorates in real-life scenarios due to varying traffic conditions. Therefore, we consider a formulation that simultaneously estimates the request's fare based on travel time and compensates the requests for late arrivals.

In this report, we investigated the benefit of ridesharing to the service provider while satisfying service quality constraints and proposed a computationally efficient single request batch assignment (SRBA) vehicle dispatch framework. Our approach provides a good balance between the system optimality and computational efficiency. The contributions of our work are summarized as follows:

- Formulate the ridesharing problem in terms of the profit obtained from a trip and optimizing the total profit of the service provider.
- Propose a computationally efficient vehicle dispatch framework for optimally assigning vehicles to requests and finding the optimal routes.
- Conduct extensive experiments with large-scale taxi data and evaluate the effectiveness and efficiency of our proposed approach by comparing it to the state-of-the-art method.

Other contributions we have made are summarized as follows:

- We employed XGBoost with Least Absolute Shrinkage and Selection Operator (LASSO) regularization for traffic volume prediction. We investigated the efficiency and effectiveness of the proposed method for different scenarios including how well it can handle variations in weather conditions and holidays. The experimental results indicated that the proposed approach was effective and efficient for predicting traffic volume. See [156] for details of this work.
- We proposed a data-driven approach for travel time prediction and analysis. We leveraged the predictive power of SVM and ARIMA to fully capture the complex patterns in the traffic data. The experimental results demonstrated the exceptional performance of the proposed approach as compared to other machine learning (ML) based techniques. See [157] for details of this work.

4.3.1 Problem Statement: In this section, some important notations and definitions are provided to mathematically formulate the profit-aware ridesharing problem.

4.3.1.1 Notations and Definitions: *Definition 1 (road network):* A road network is represented as a directed graph $G(N, A)$, where the node set N denotes road intersections, and the arc set A denotes road links. Each arc $(i, j) \in A$ is associated with a travel cost.

Definition 2 (request): A request r is represented by a tuple (o_r, d_r, t_r) , where o_r is the pickup location (origin), d_r is the drop-off location (destination), and t_r is the time the request is sent by the passenger.

Definition 3 (vehicle): A vehicle v is represented by a tuple (q_v, κ_v, s_v) , where q_v is the vehicle's current location, κ_v is its capacity, and s_v is its current schedule.

Definition 4 (trip): A ride-sharing trip $\mathcal{T}$ refers to a set of requests that can be grouped and served by the same vehicle.

Definition 5 (schedule): The schedule $s_{v, \mathcal{T}}$ of a vehicle v refers to the order of picking up and dropping off requests in a trip. For a particular vehicle v , there may be multiple schedules to assign. To determine whether a schedule is feasible or not, the following constraints should be satisfied:

- The origin of a request must be visited before its destination.
- Each request's maximum waiting time should not exceed a certain threshold Ω .
- Each request's total travel delay δ_r should not exceed a certain threshold Λ .
- The vehicle's capacity κ must not be exceeded.

The set of all feasible schedules of vehicle v is denoted by S_v and the optimal schedule is s_v^* .

4.3.1.2 Constrained Profit Optimization: Given a vehicle fleet $V = \{v_1, \dots, v_m\}$, a set of requests $R = \{r_1, \dots, r_n\}$, and a set of feasible schedules S_v for each vehicle, the objective is to maximize the system's profit by assigning high profit schedules to vehicles. The optimal assignment of schedules to vehicles can be obtained by solving the following integer linear program (ILP):

$$\operatorname{argmax}_{x_{v,s}, \epsilon_r} \sum_{v \in V} \sum_{s \in S_v} x_{v,s} \cdot p_{s_v} - \sum_{r \in R} \epsilon_r \rho_r \quad (4.1)$$

$$\text{s.t.} \quad \sum_{s \in S_v} x_{v,s} = 1, \quad \forall v \in V \quad (4.2)$$

$$\sum_{v \in V} \sum_{s \in S_v} x_{v,s} \cdot \Phi_s(r) + \epsilon_r = 1, \quad \forall r \in R \quad (4.3)$$

where p_{s_v} is the profit of the vehicle's planned schedule s_v , ρ_r is a very large value for penalizing rejected requests, and a binary indicator function $\Phi_s(r) \in \{0, 1\}$ which determines whether $r \in s$ or $r \notin s$ is introduced. The binary variable $x_{v,s} \in \{0, 1\}$ indicates whether a schedule is assigned to vehicle v ($x_{v,s} = 1$) or rejected ($x_{v,s} = 0$). The binary variable $\epsilon_r \in \{0, 1\}$ indicates whether a request r is assigned ($\epsilon_r = 0$) or rejected ($\epsilon_r = 1$). Constraint 4.2 ensures that each vehicle v is assigned exactly one schedule and constraint 4.3 ensures that no request is assigned to more than one vehicle.

The profit of a schedule p_{s_v} is computed as:

$$p_{s_v} = \sum_{r \in T} [fare(r) - penalty(r)] - cost(s_v) \quad (4.4)$$

where $fare(r)$ is the amount request r pays, $penalty(r)$ is the compensation r receives due to late arrival, and $cost(s_v)$ is the expense of providing the service.

4.3.2 Proposed Method: In this section, we briefly describe the proposed vehicle dispatch framework.

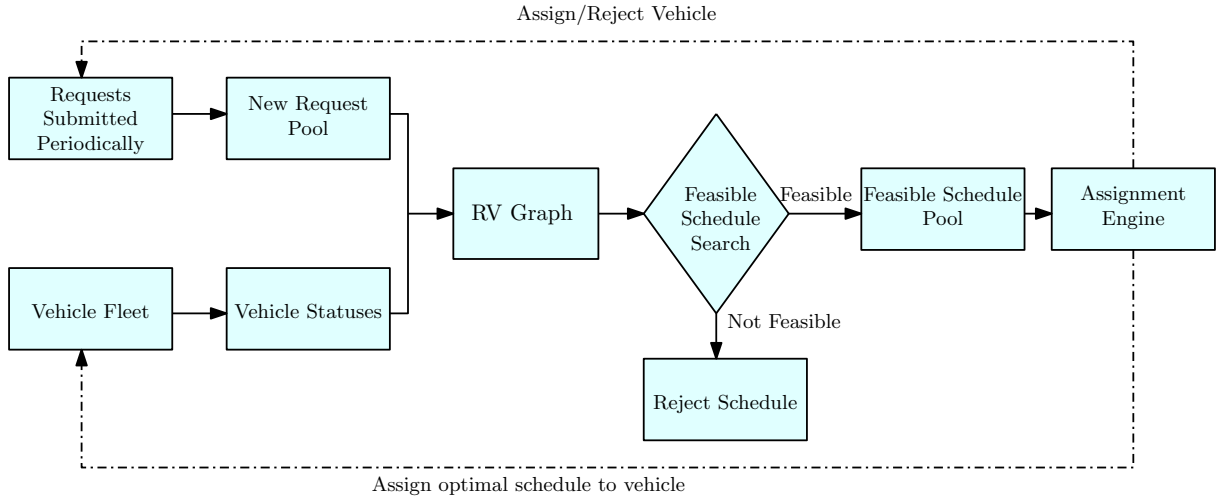


Figure 28. Schematic overview of vehicle dispatch logic.

We employ the concept of single request batch assignment (SRBA) where incoming requests are allocated to vehicles in a one-to-one manner. Our framework can be summarized into four main steps: (1) collection of requests, (2) computation of a pairwise request-vehicle (RV) graph, (3) exploration of feasible schedules, and (4) solving an integer linear program (ILP).

(1) *requests collection.* Requests are submitted periodically (e.g. every 60 seconds). New requests received within the given time period are stored in a pool to be assigned to a vehicle while factoring the vehicle's current position and schedule.

Table 15. System Parameter Settings (default values in bold).

Parameters	Settings
Max Waiting Time Ω (s)	120, 180, 240, 300
Batch Period (s)	30
Capacity κ	2, 4 , 6, 8
Instance Scale ($ R , V $)	(400k, 2000)

(2) *RV-graph*. The RV-graph proposed in [19] is considered in our implementation. The RV-graph finds different combinations of requests and vehicles that can be pairwise-shared. Two requests r_1 and r_2 are connected if they can be served by the same vehicle whilst ensuring that the constraints are not violated. Similarly, a vehicle v and a request r are connected if v can serve r without violating the constraints.

(3) *feasible schedules search*. For each vehicle v , and new requests received, we find the set of all feasible schedules S_v .

Therefore, this approach effectively reduces the solution space for the optimal assignment of schedules by pruning all infeasible schedules.

(4) *assignment engine*. The feasible schedules of each vehicle obtained from step 3 is fed into an assignment engine. The ILP formulated in 4.3.1.2 is solved to obtain the optimal schedule set $S_V^* = \{s_{v_1}^*, \dots, s_{v_m}^*\}$ of all available vehicles.

4.3.3 Experimental Study: In this section, we examined and compared our proposed method with the state-of-the-art multiple batch assignment technique [167] and a travel distance based single request batch assignment method. We run all experiments five times [167] on the same machine to guarantee a fair comparison.

4.3.3.1 Simulation Details: The ridesharing environment was simulated based on the settings in [273]. At the onset of the simulation, the initial positions of the vehicles are distributed uniformly in the road network. We used the Dijkstra’s algorithm to compute the shortest paths between all nodes. The pickup and drop off times of the taxi trips are used to compute the travel time of each road link for the time of the day. The travel time information of each road link is used to compute the mean and standard deviation of a route.

Table 15 provides a summary of the main experimental control parameters [167]. The maximum travel delay is set to be twice the maximum waiting time $\Lambda = 2\Omega$.

4.3.3.2 Algorithm Comparison: We evaluate the effectiveness and efficiency of our proposed framework by comparing with the state-of-the-art vehicle dispatch framework:

- **OSP:** [167] Optimal Schedule Pool. This approach groups multiple requests into trips and computes their optimal schedules to be assigned to a vehicle.
- **SRBAD:** Single Request Batch Assignment with Travel Distance. This approach computes the fare per request based on the travel distance from the request’s origin o_r to its destination d_r .
- **SRBAT:** Single Request Batch Assignment with Travel Time. This is the proposed approach which considers travel time in estimating the fare per request.

4.3.3.3 Results: We provide a comprehensive analyses of the performance of our proposed approach as compared to the OSP framework. Additionally, we compared our approach which incorporates travel time with a single request batch assignment which incorporates travel distance in estimating the request’s fare. The performance metrics considered include the profit generated to the service provider and the response time of the algorithms. We evaluated the algorithms by varying the parameters shown in Table 15.

Fig. 29 shows the results of varying maximum waiting time. In Fig. 4.29(a), the amount of profit generated increases with increasing maximum waiting time for both SRBAT and OSP. Profit increases because passengers are tolerant to longer waiting times, and travel delay constraints, therefore, more requests are served. On average, the OSP framework generates 2.97% more profit than the SRBAT framework for varying maximum waiting time. Fig. 4.29(b) indicates that the response time of SRBAT is almost constant while that of the OSP increases linearly. On average, SRBAT is approximately four times faster than OSP.

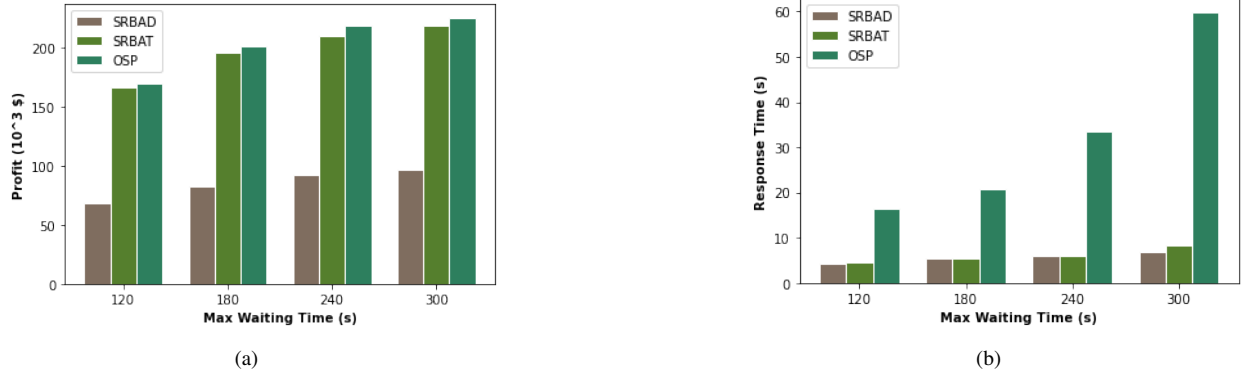


Figure 29. Comparison of performance for varying maximum waiting time.

Fig. 30 shows the results of varying vehicle capacity. Fig. 4.30(a) indicates that both SRBAT and OSP generate more profits with higher vehicle capacity. It implies that with higher capacity vehicles, more requests can be served and consequently, more profits generated. It should be noted that there is no significant difference in the algorithms' performance when the vehicle's capacity is increased beyond the default value ($\kappa = 4$). On average, the OSP framework generates 3.87% more profit than the SRBAT framework for varying vehicle capacity. On the contrary, Fig. 4.30(b) shows that the response time of SRBAT is almost unchanged while that of OSP increases linearly. On average, SRBAT is approximately nine times faster than OSP for varying vehicle capacity.

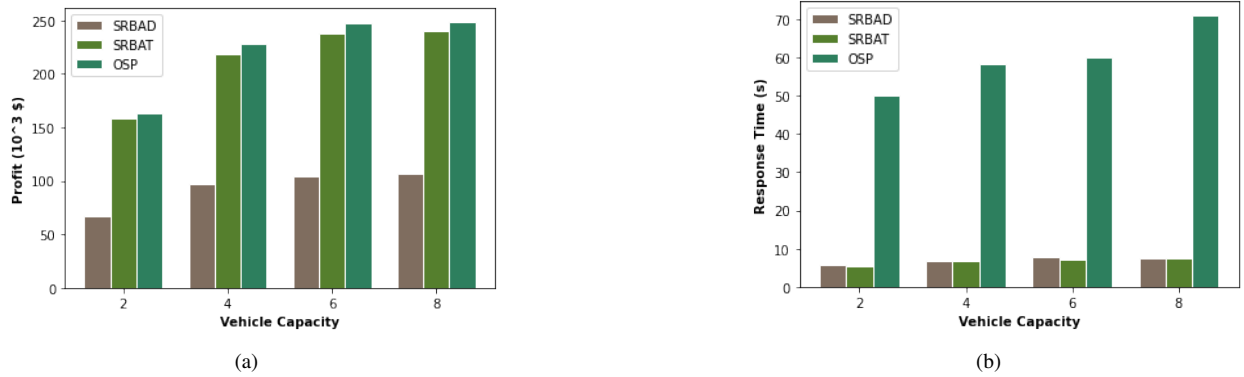


Figure 30. Comparison of performance for varying vehicle capacity.

Further Analysis. We present a comparison of the SRBA approach when the fare per request is estimated based on the travel time and when based on travel distance. In Figs. 4.29(a), and 4.30(a), it can be clearly observed that SRBAT achieves a significantly higher amount of profit than SRBAD. This is because computing fare based on distance is fixed whereas based on travel time varies with the traffic condition at that moment. Nevertheless, in Figs. 4.29(b), and 4.30(b) we observe that there is no significant difference in the response time of SRBAT and SRBAD. It implies that the response time of the SRBA framework is not affected by how the fare per request is computed.

4.3.3.4 Time Complexity Analysis: The OSP vehicle dispatch algorithm consists of combining requests into trips and computing a graph of trips and potential vehicles to serve them. The time complexity of this step in the worst-case is $O(m\kappa N_T N_{r_{T_k}})$, where m is the fleet size, N_T is the number of trips, and $N_{r_{T_k}}$ is the number of requests in trip k which is responsible for the high computational burden of OSP.

4.3.4 Conclusion: In this report, we proposed a computationally efficient, dynamic ridesharing framework which optimizes the system's profit. We presented a profit optimization formulation that computes the fare per request based on the travel time from the request's origin to its destination. Numerical experiments performed on the large New York City taxi dataset demonstrated that the proposed framework is up to ten times faster than the state-of-the-art framework and achieves comparable profits. Therefore, the proposed framework provides a good balance between the system's profit and the response time.



Figure 31. Hardware-in-the-loop simulator setup.

4.4 Task 3: Development of a Testbed for Cooperative Control of CAVs/UAVs

4.4.1 Development of hardware-in-the-loop Simulator: Driving simulators offer the advantage to investigate the interaction between real drivers and virtual vehicles as well as virtual traffic, at an early stage of development, and without the need of prototype vehicles. Furthermore, functional and human machine interface (HMI) related research questions can be addressed in a safe and realistic environment.

Driving simulators are classified in different categories, ranging from static desktop simulators to complex, highly dynamic simulators with multiple degrees of freedom for lateral and rotational movements. The vehicle mock-up designs vary from a basic steering and pedal setup to a complete modification of a full vehicle. For this task, a static full vehicle driving simulator is selected based on the targeted research fields, space availability and cost efficiency. Therefore, the goal of this task is to design, construct, and operationalize a static, full-vehicle driving simulator.

Supported by College of Engineering at NC A&T, and in collaboration with a Silicon Valley company, we are developing a state-of-the-art hardware-in-the-loop simulator for CAVs including a full vehicle and several human driver stations to simulate the mix of AV and human driver cars. This simulator is installed in the Engineering Research Innovation Center (ERIC), a new building at NC A&T State University. The rendering in Figure 31 shows the simulator setup in a high ceiling darkened environment to produce highly immersive test scenarios. Some of the main features of the simulator that are aligned with our research fields are

- The average delay from a driver's input to a visual update according to that input is below 35 ms
- The simulator covers a visual representation of the front view as well as the rear view for the side mirrors and the rear view mirror.
- There are three additional manual operator workstations which can synchronously drive cars along with the ego car to simulate mixed traffic (manned and unmanned surrounding traffic).
- The simulator will be capable of working with extra measurement devices such as eye-trackers or leap motion sensors in order to generate data which later can be used to analyze driver behavior.
- The bi-directional interface between the mockup and the simulator components cover force feedback signals that match the actual driving situation. It will also cover signals for the instrument cluster and secondary driver inputs (e.g. indicator lever and automated driving mode button).

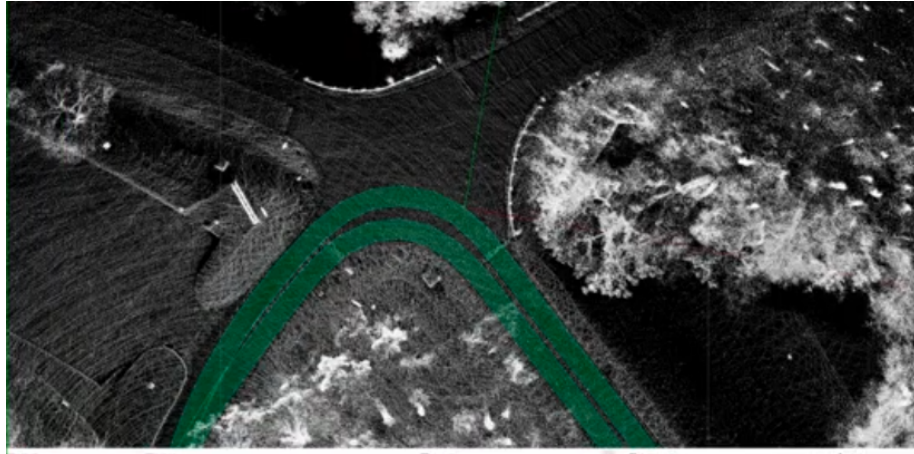


Figure 32. Lidar/Pointcloud map for localization.

- The simulated environment is created using the software environment VTD by Vires/MSC, for which a full educational license is procured as proposed by Vires/MSC during the preparation of the project. This software tool allows us to create various road tracks and scenarios in urban and highway environments.

4.4.2 Development of a CAV testbed of autonomous vehicles: Development of a CAV testbed for autonomous vehicles requires a fleet of vehicles, various sensors, communication devices, computing systems and a testing ground. The fleet of vehicles in the testbed include three shuttles (Polaris GEMe6) and one mid-sized vehicle (Pacifica). Each of the vehicles in the testbed are equipped with sensors, communication devices and onboard computers with proper drivers and software stack to enable autonomous driving. Thus the development of the CAV testbed involves

- Installation, operationalizing and testing of hardware components
- Development and testing of software components
- Installation, operationalizing and testing of communication devices
- Integration of the hardware and software components the CAV testbed

4.4.2.1 Installation, operationalizing and testing of hardware components: The CAV testbed hardware components consist of various sensors, computing platform, sensor mounting and all the power and signal cabling and connections. Some of the hardware components/sensors are placed outside the vehicle such as the Lidar, Radar, Cameras and GPS antennas on a proper mounting frame attached to the structure of the vehicle while the computing platform and other electronic components are placed inside the vehicle. After selecting proper placements of each of the sensor units configuration and calibration have been done for optimized sensing.

4.4.2.2 Development and testing of software components: The CAV testbed software components are grouped into three major categories based on functionality; Perception, localization and planning, and control. The perception subsystem uses the camera, lidar and radar sensors to understand the environment such as detecting obstacles, traffic signs and signals. This software component is being tested independently for pedestrian detection and traffic signals before integrated with the complete software stack. The localization and planning subsystem uses the GPS, lidar sensor and map data to determine the navigation path. Localization maps are already created for driving test areas as shown in Figure 32, and the localization and planning software stacks are also being tested. The last subsystem is the control software stack which actuates the steering, braking and acceleration based on the planned path. This component is fully tested and only minor adjustments can be made as desired.

4.4.2.3 Installation, operationalizing, and testing of communication devices: For efficient operation of the vehicles, each of the shuttles will be equipped with a 5G communication device (hotspot) which enables them to securely communicate with each other and a control room over a network as shown in Figure 33. For this purpose we are investigating the Inseego 5G MiFi device to determine data transmission capacity (maximum bandwidth) and its

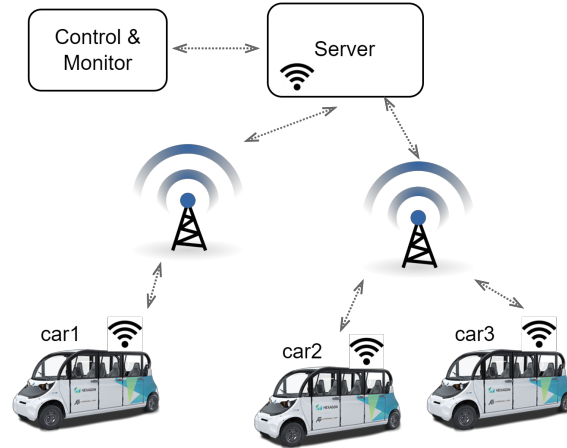


Figure 33. Communication of CAVs.

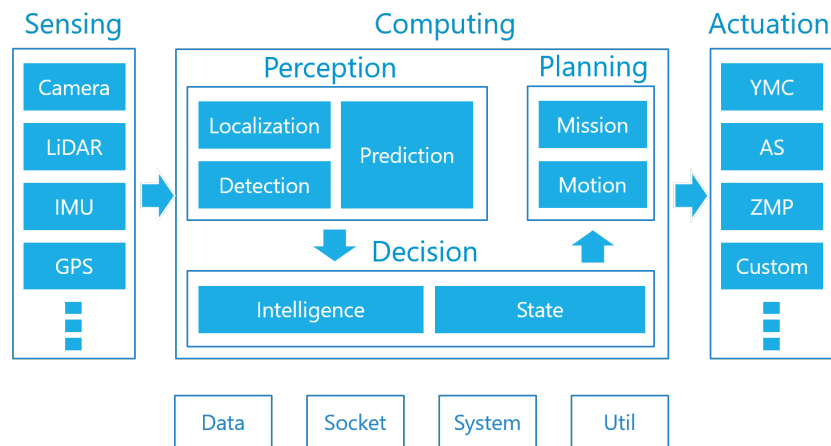


Figure 34. Autoware software architecture.

connection reliability as the vehicles move in different places. This helps us prioritize the type of data to transmit and identify the fallback strategies in case of delayed and failed communication. Preliminary test results indicate that low volume of data can be communicated in real time (with tolerable delay).

4.4.2.4 Integration of hardware and software components: Autonomous driving software stack (Autoware) is used for integration of various components of the CAV. The Autoware stack, shown in Figure 34, is a complete software stack for research & development of AVs. We chose to use this software to quickly test the complete hardware-software setup while developing other software components of our own without the need to start from scratch. All the sensor units (Lidar, Cameras, Radar and GPS) are configured, installed and integrated with the Autoware software stack to achieve the complete autonomous driving system. The integration has been tested and validated using several practical tests on each vehicle platform. With this integration, each of the vehicles are able to navigate predefined paths while stopping for obstacles and stop traffic signs demonstrating the basic functionalities of autonomous driving.

4.4.3 Development of an in-house AV testbed: Under the task of development of an in-house AV testbed we purchase an electric Gem e2 car and made implement drive-by-wire automation. The high-level specification about the Gem e2 car automation for CAV is described in this section. We implement the drive-by-wire technique on Gem e2 car by applying the following steps:

- Accelerator pedal control using a drive-by-wire technique

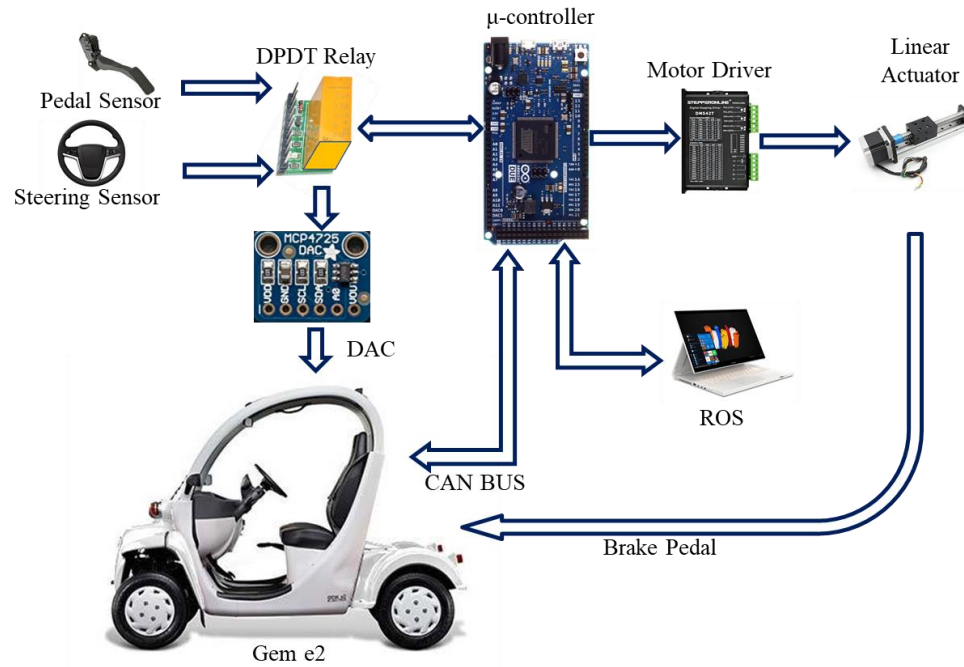


Figure 35. Development of a Testbed for Cooperative Control of CAVs with Gem e2 Car

- Steering wheel control using a drive-by-wire technique
- Brake pedal control using a drive-by-actuator technique

The high level information of overall interfacing is shown in Figure 35. The peripheral sensors and actuators of the car are operated by an embedded 32-bit micro-controller with five kinds of interface channels: a) four (two + two) analog to digital voltage connections are used for reading the steering wheel and the accelerator pedal sensors, respectively b) four (two + two) digital to analog connections are used to generate analog voltages to control for steering and accelerating the car, respectively, d) a linear actuator receive commands for controlling hydraulic brake by generating back and forth motion on the brake pedal, e) two DPDT relay based switching mechanisms is used to switch between autonomous and manual modes of the car, f) finally, a CAN-bus interface is used to retrieve real-time information about the car's speed, the current position of the steering wheel, and other data. All five interfaces are connected to a 32-bit micro-controller that provides a Serial interface to the ROS powered control-computer.

The software architecture of this testbed is based on an open platform for developing, deploying, and running different applications. Our developed software architecture (i) is easy-to-install and multiple-platform compatible with modular tools, (ii) is ROS compatible, (iii) enables the analysis of the errors and isolation of the faults, and (iv) can be easily expanded with new sensory devices. We designed the car autonomy framework in a way that the car can be driven in three modes – a) in manual mode, it can be driven by a person as a regular car, b) in remote-control mode, it can be driven by a person using a joystick connected to the ROS powered computer, c) finally, in autonomous mode, a ROS powered controller can autonomously send commands from a control computer to the embedded micro-controller. We designed and implemented a relay control circuit that can switch the car between remote-control mode and manual mode. In remote-control mode we can control the acceleration and brake either by using a raspberry pi4 or a laptop directly. We interfaced a display and a joystick with raspberry pi4. We used a joystick to provide accelerator command and brake command to the ECU of the Gem e2 car via the Arduino Due micro-controller board. In remote-control mode we can also control the car using keyboard commands from a laptop.

4.4.4 Enhancing the perception and safety of CAVs: We also continued our work on Developing techniques for AV/CAV perception, by detecting pedestrians using fusion on multiple different networks. There have been several methods with impressive object detection and semantics segmentation performances to perceive

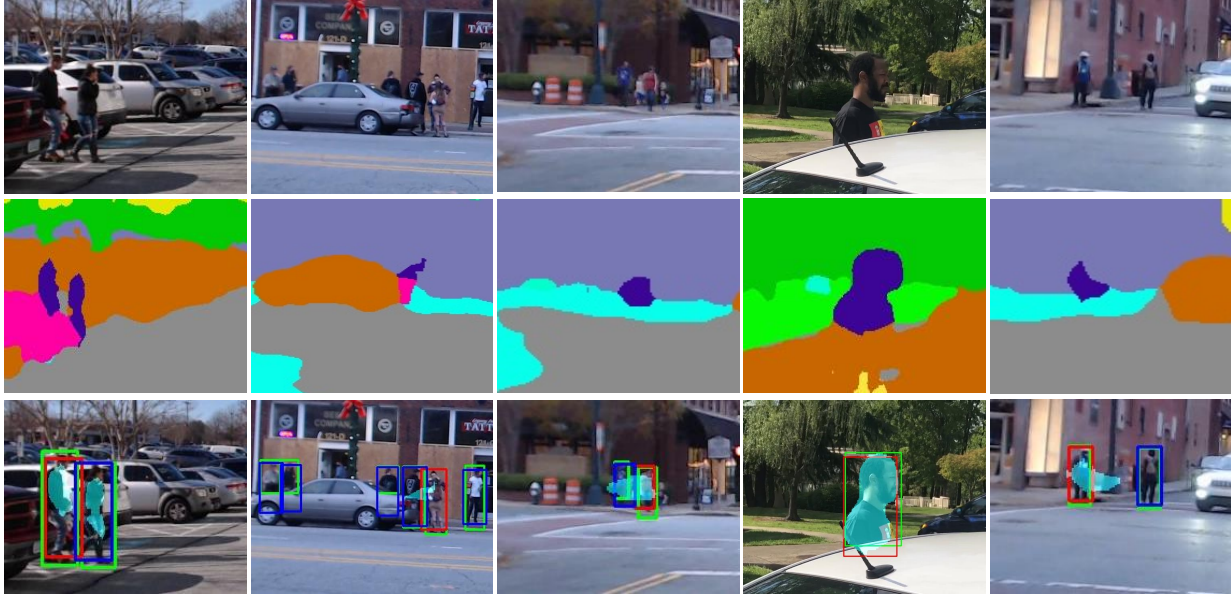


Figure 36. **Detection comparisons:** The top row represents the input images. Then, the middle row indicates the corresponding semantic map of input images. Finally, the bottom row shows the ground truth, baseline detection, and detection with the fusion mechanism. Green, blue, and red color bounding boxes represent ground truth, baseline detection, and improvement with fusion, respectively.

the surrounding of a autonomous vehicle [134, 135]. These perception systems facilitate the control system of autonomous vehicles [70, 71, 217]. We hypothesize that we can take advantage of the capabilities of these individual detection methods and improve their performances when they are properly fused. We proposed a fusion method that combines anchor-based prediction with high-level semantic information. In our fusion method we apply a consensus-based scoring technique that fuses pair-wise pixel-relevant information from the object detector and the semantic segmentation network to boost the final confidence scores. The parallel implementation of the object detection and semantic segmentation networks in the proposed framework entails a low runtime overhead. The efficiency and robustness of the proposed fusion framework are extensively evaluated by fusing different state-of-the-art pedestrian detectors and semantic segmentation networks on a public dataset. The generalization of fused models is also examined on new cross pedestrian data collected through an autonomous car. Results show that the proposed fusion method significantly improves detection performance while achieving competitive runtime efficiency. Figure 36 showcases detection results of one of the pedestrians detectors and its improved results after fusing with one of the semantic segmentation networks. We published a journal paper based on our work in IEEE Transaction on Intelligent Transportation Systems [133].

4.5 Task 4: Aerial traffic monitoring using CAVs

Since determining the number and type of vehicles on a road or in parking lots is the basis for planning and implementing highway infrastructure construction, safety policies, and any other traffic management activities, the road transportation research and development community gives particular attention to vehicles' characteristics and interaction within a traffic flow. For instance, the volume of traffic (number of vehicles in traffic stream) at junctions, parking lots, or road segments are the basic yet powerful pieces of information needed by transport engineers. These data are commonly collected over a specified period of time frame and duration. These traffic characteristics are interesting and crucial for applications in traffic management regulations, which in turn improve utilization and road users' safety.

Commonly, studies on traffic volume and speed typically use sensors mounted on traffic lights or detectors buried in the pavement. Due to its immobility and expensive installation and operating costs, these traffic monitoring devices have been improved and replaced by better devices and approaches. Moreover, the traditional highway vehicle monitoring measurement equipment has a lower measurement accuracy, and is more prone to flawed readings. One of the latest introduced methods of traffic measurement is using unmanned aerial vehicles (UAVs).

One of the blessings of adopting UAVs for traffic is the capability of “bird’s eye” view. Bird’s eye view is vital input data for vehicles’ tracking trajectories in a traffic stream. Determining the paths taken by cars in gridlocked traffic is essential for studying traffic dynamics. For the safety and capacity analysis of road junction layout, vehicle trajectory is especially important. However, traditional methods encounter difficulties to determine such precise vehicle courses in congested traffic situations due to the fact that most of them lack “top-to-down” (birds eye) views of the intersection. Also, video traffic surveillance as one of traditional methods suffers from occlusion, false defections, and tracking errors depending on installation height/location. In addition, the development of modern transport monitoring technology has created opportunities to shorten the time needed to collect and analyze the traffic data necessary for traffic management, which provides strong instruments to manage highways to maximize their use to the fullest capacity, minimize vehiclerelated urban problems including congestion and road accidents. UAVs, also known as Drones, are one of the most versatile and dynamic new technologies of the modern era. frequently adaptable and can be utilized to collect data at difficult road intersections and in difficult traffic data collection circumstances. In addition, they are able to acquire crucial traffic parameters and high definition footage of the multiplex roadways from a top-down perspective than any other monitoring technique. Additionally, UAVs can be modified to continuously monitor important highway stretches at critical times of traffic operation. In general, the use of UAVs to identify, track, and locate vehicle targets has greatly benefited traffic monitoring efforts because such information is typically challenging to obtain (Liu & Zhang, 2021). Costwise, UAVs provide cost saving benefits than conventional systems since they are mobile platforms that can be utilized to collect data at different locations everywhere they are needed. This is true as UAV based traffic monitoring does not involve installation, removal and reinstallation costs, and these systems are not installed at fixed locations unlike most of the conventional methods. Thus, compared to traditional approaches, UAV-based traffic studies have been shown to be more cost-effective. Additionally, the data obtained by UAVs is described as being detailed and not requiring substantial reading correction. Additionally, the problem of finding trustworthy trajectory data has been resolved with the development of UAVs for vehicle course tracking. The road environment, including nearby vehicles, shadows, traffic signs, and infrastructure, is the main culprit of incorrect vehicle detection. Multi-rotor UAVs’ exceptional top-down vision and hovering capability have helped them avoid occlusion and false detection issues in a big way. Because they can hover above traffic, they can get good coverage and less distorted data. These data demonstrate the superiority of UAV-based traffic monitoring systems over competing technologies. Additionally, applying computer vision and machine learning techniques to the data processing task can significantly speed up the inference process.

4.5.1 UAV-based Traffic Monitoring Framework: This section’s main objective is to propose a conceptual framework for automated traffic monitoring using UAVs as a data collection platform. Many frameworks have been proposed to detect particular traffic factors, and numerous studies on UAVs for transportation applications have been conducted. Dahl & Javadi (2019), for instance, proposed a speed measuring model based on intrusion lines from video data captured by a UAV [64]. The camera’s frame rate, as well as the location and quantity of intrusion lines, affect the framework’s accuracy. By comparing the outputs of the probability density function with the outcomes of a simulation of the related movements, the approach also computes a speed probability density function to validate the framework. However, this framework only functions for speed measurements and appears to be more appropriate for data from fixed traffic camera installations. In order to extract the trajectories of several vehicles on a specific road segment, Khan et al. (2017) suggested a methodological framework for UAV video processing [144]. The framework is divided into five phases, starting with picture rectification, region of interest masking, and trimming as pre-processing techniques. Image stabilization comes next. The data is scaled once the photos have been geo-registered and stabilized. Then, to find and track moving items of interest in the image, vehicle detection and tracking is used. The vital processes needed before and during data collecting, however, were overlooked in this investigation. Even though research has been done, there is limited literature on survey-based studies that may be used to review the work done on UAV-based traffic applications and provide frameworks for UAV-based traffic study. Proposal When conceptualizing a methodological framework for improved guidance, we uphold that the protocols for UAV-based traffic monitoring activities must be succinct but comprehensive. In this work, we present a methodology that organizes processes and sub-tasks based on the core of the activities and aims to be all-encompassing and universal. The planning and data gathering stage, the pre-processing stage, and the data process automation stage make up the conceptual framework’s three stages, as the framework’s schematic is shown in Figure 37. Planning and Data Gathering The workflow is divided into three sections, the first of which is planning and data gathering. Definition of the scope, planning, and implementation of the actual data collection are these. Research Type and Location Identification: Prior to beginning any operations, it is important to identify the type of traffic study that is being planned, or the necessary traffic

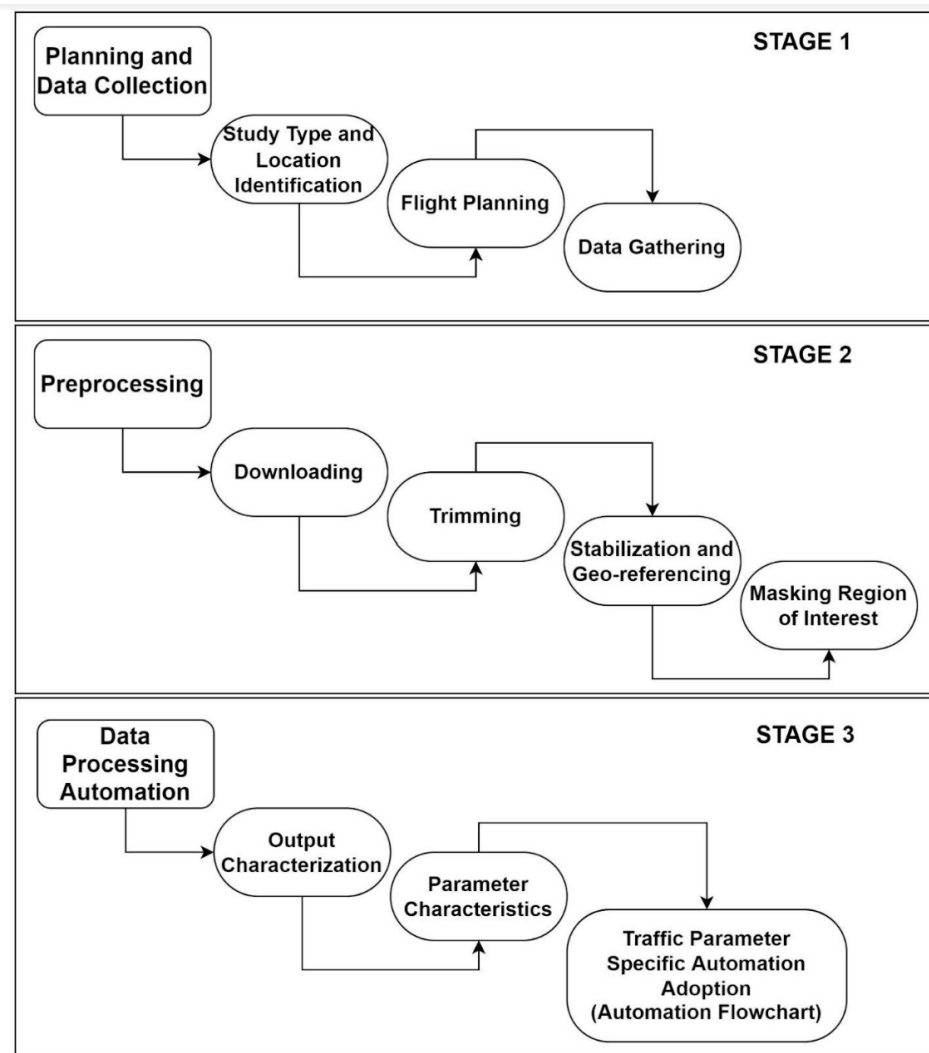


Figure 37. UAV based traffic monitoring conceptual framework.

parameters. The necessity for the study is first addressed by determining the traffic parameters that will be studied. The study area will next be framed to clearly define the location scope, which is the other crucial element needed to check the regional UAV flying regulations for the study area. Consequently, the information on UAV flight regulations determines whether or not a special permit is required.

Hardware, spatial, and temporal planning are the three types of planning covered by this work. Hardware Planning: After the data type and quality are taken into consideration, hardware needs should be made. The UAV, the sensor, and any additional components that go with them are all part of the hardware requirements. Using the local flying zone maps, you should be able to determine the flying zone category and a safe distance from sensitive installations based on the study area. Therefore, the major factors used to determine flight parameters, such as flying height and spatial resolution, are geographical features such as infrastructure type, built-up area extent, tall building height, and vegetation presence. Temporal planning entails deciding on a time when the weather will be acceptable, the time of day the study will be conducted, and the length of time for data collecting. Additionally, the temporal planning includes the temporal resolution, which is the amount of flights at various hours of the day. As a result, the kind of traffic research that is intended to be conducted determines the temporal resolution. After that, the UAV is used to start gathering data. With the help of the radio controller or the autopilot, the flight can be managed manually or automatically. Here, extra care should be made to ensure that the recorded data (video or image) covers the planned flight path and is steady and free from shake.

Pre-processing is done to make the actual data processing stage easier. It aids in saving money and time during data processing. After data collection is complete, the UAV either downloads the completed data straight from

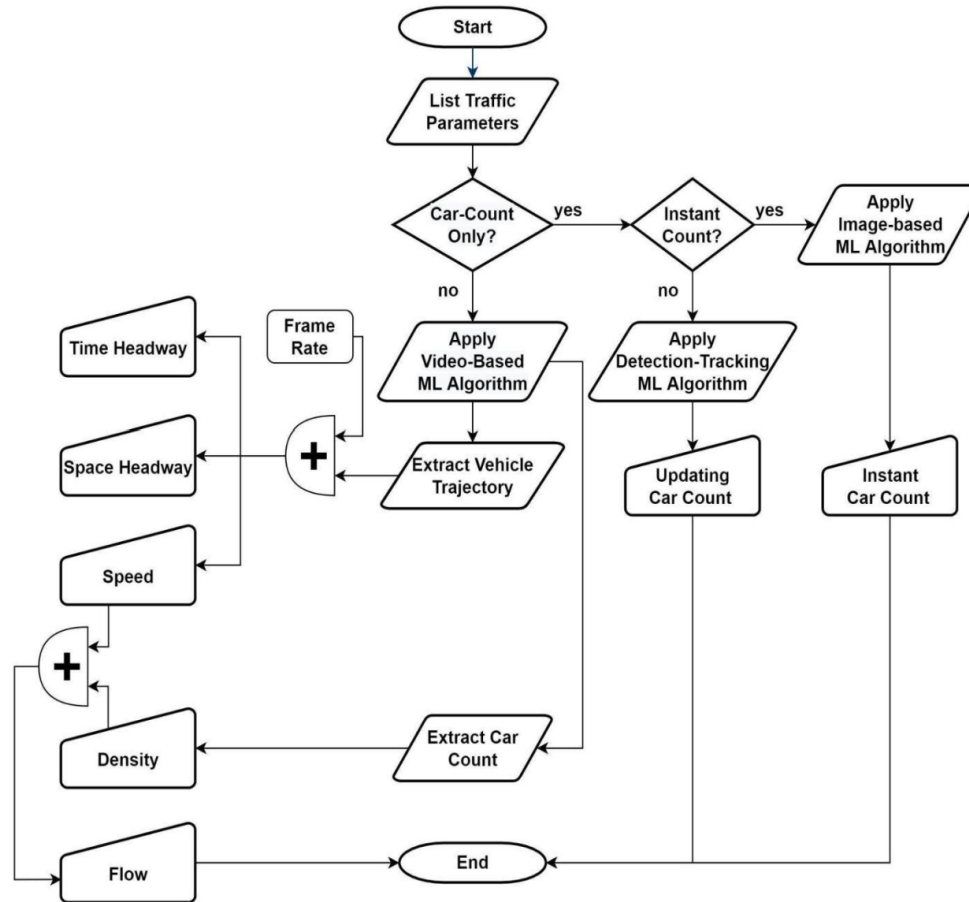


Figure 38. Traffic parameter specific automation process flowchart

the drone or online via cloud storage. The kind of data relies on the type and scope of the investigation. But pictures or videos are the most typical types of data gathered for traffic studies. In this scenario, the captured video or image should be downloaded along with the flight telemetry data. The position, orientation, and flying altitude of the UAV are all included in the flight telemetry data. When the data format is video, trimming and stabilization are tasks that must be performed. Trimming is the process of removing extraneous video content, including the takeoff and landing sequences. Additionally, the data needs to be stabilized if it shakes while being captured, which can happen due to wind gusts or rotor vibration. Thus, stabilization is necessary to create still photos in order to reduce the impacts of camera shaking and increase the effectiveness of tasks that will be completed in advance. You can use a variety of open-source tools to stabilize video data. Then, the pixel coordinates of the image are given real-world distances and positions through georeferencing. By creating the data in an actual scale and direction, it allows the user to visualize and estimate traffic factors. Before flying the UAV, create ground control points to georeference the photos. To further improve processing efficiency, masking regions of interest are applied to the image data, which often eliminates the backdrop of the image. It will make it possible for the computer vision algorithm to concentrate on the subject of interest in the visual foreground. This approach reduces the burden required for computing and, thus, its cost.

4.5.2 Automation of Data Processing: UAV image data processing employs extensive machine learning applications with the goal of producing useful data for transportation-related decision making with a relatively small investment of time and resources. Computer vision techniques are used in data processing automation to find and track moving objects. The general data processing automation processes are shown in Figure 38.

Application of the Computer Vision (CV) Algorithm in Phase 1: Vehicle detection and tracking are the two main uses of computer vision algorithms. There are many different computer vision algorithms available. The effectiveness of a particular method, however, is dependent on the nature and details of the project and data, hardware performance, and anticipated outputs (Szeliski (2010), Bouguettaya et al. (2022)). Deep learning-based versions of detecting algorithms predominate. Examples include Regional Proposal Convolutional Neural Network (Grishick et

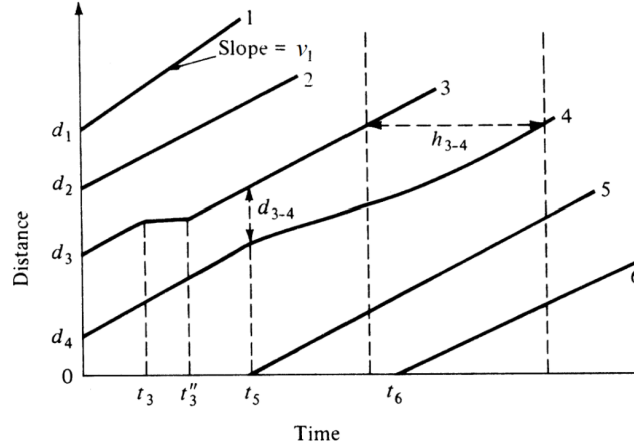


Figure 39. Example of vehicle trajectory plot

al. 2014), Deep Neural Network (Liu and Chang 2019; Zhang et al. 2020), You Only Look at Once (Redmon and Farhadi 2018), Fast R-CNN (Grishick et al. 2015); Faster R-CNN (Ren et al. 2015; Ren et al. (2017)), and Mask R-CNN detector (He et al. The various techniques used for vehicle detection are shown in Table 1. The number of vehicles found and their location in the frame will be the first results of the detection algorithms after they have spotted autos. The next most crucial step in subsequent frame detection is to determine, based on the Euclidean distance of their feature vectors, whether the identified items in the second frame are the same ones from the first or whether they are brand-new objects that have entered the region of interest. Its position will be updated if the item in the current frame is the same as it was in the previous frame; if it is a new object, it will be identified specifically and its position will be noted. Tracking is the name given to this activity. Vehicle counts and trajectories, which are the results of computer vision algorithms, are utilized to derive traffic characteristics. As a result, the first level outputs include the video frame rate as well as instant or updated vehicle counts and positions within successive frames. Traffic density, speed, and flow can be calculated using these data as follows:

$$k = N/L$$

Where, k is the traffic density [number of vehicles per mile], N is the number of vehicles in region of interest [number of vehicles], and L is the length of the region of interest [miles]. Speed of a vehicle can also be computed as:

$$v_i = fps * FR$$

Where, v_i is the speed of a vehicle [pixels per second], fps is the Euclidean distance for change of position between the reference frames [feet], and FR the reference frame rate [frame per second]. Using georeferencing information the speed can then scaled to feet per second. Moreover, flow can be computed using the harmonic speed mean (also known as space mean speed) and density.

$$V_s = N/(1/v_i)$$

$$V_s = N/(\sum_{n=1}^1 1/(v_i))$$

$$q = C * k * V_s$$

Where, V_s is the space mean speed [feet per second], q is the flow [vehicles per second], and C is a unit conversion factor equal to 5280. In addition, vehicle trajectory output can be plotted against time (Figure 39).

In figure 39, the numbers represent different vehicles' ID, the horizontal distance h_{3-4} represents the time headway, and the vertical distance d_{3-4} represents the space headway between vehicle three and four. Vehicle Counting Application Instant counts, often referred to as image-based volume analysis, are carried out while dealing with stationary vehicle targets, such as parking lot automobile counting. For these types of research, the UAV must photograph the location during the precise time of day that is required by the study's design. UAV photos are of a very high resolution, necessitating

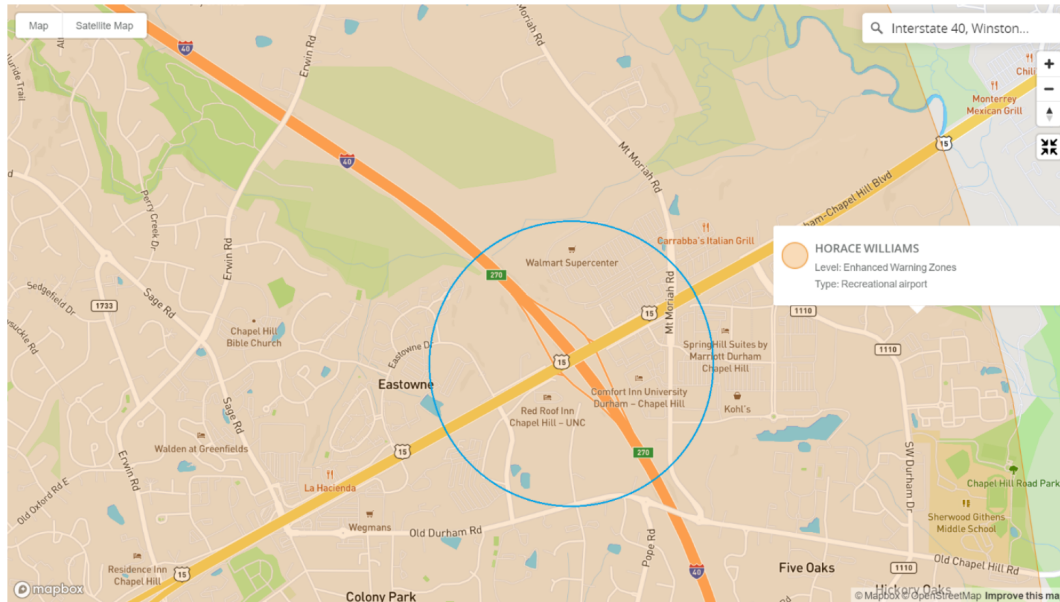


Figure 40. DJI's GEO System flying zone delineation for the I40 study area [76]

the use of appropriate automatic processing techniques. To limit the locations where cars might be detected, Thomas Moranduzzo (2014) proposed a method that included an asphalted zone screening step, a feature extraction procedure based on scalar invariant feature transform (SIFT), and an application of support vector machine (SVM) to classify observed keypoints [216]. The SIFT is a feature detection system to find and describe local features in an image that was released by David Lowe in 1999 [194]. Keypoints of interesting things are therefore extracted from the image. Then, based on the Euclidean distance between the feature vectors of the keypoints, an object is identified in a fresh image. A probability that a specific set of features is present in the detected image is output by the method. Additionally, characteristics are classified using the SVM classifier, one of the supervised learning techniques. Thomas Moranduzzo (2014) used the SIFT to first determine a set of keypoints in the image under consideration, then the SVM to distinguish between keypoints assigned to automobiles and others [195]. Traffic counting using video is useful when real-time vehicle density and change over time are needed, video-based volume analysis is carried out. The difficulty of this task exceeds that of image-based analysis. The automation process involves updating count while tracking changes between video frames over time. It also involves working with a vast amount of data. Implementation of Vehicle Automated Counting for Video Input Data The suggested architecture is tested in this research using field data gathered using a multi-rotor UAV and an automated vehicle counting technique.

Identification of the parameter: The traffic parameter that is supposed to be identified is traffic volume. The volume of traffic denotes the quantity of vehicles on a certain road. The size and price of all types of road transport infrastructure are determined by this simple yet effective criteria. Other traffic engineering characteristics are driven by traffic volume as well. Two research regions have been chosen for this study's location. The first research area is Exit 270 of Interstate 40, where the westbound lanes are examined. Here, a left lane drops from three to two lanes (figure 40). The second position was at Exit 13 of Interstate 440, gazing westward at the outer ring (figure 41). **Spatial Planning:** The data collecting team from the NC DOT has looked into any unique authorization requirements for these two locations. A 2 km radius circular area extension of the Authorization zone, the I-40 study region is designated as an Enhanced Warning Zone. Enhanced Warning Zones do not require permission to use drones, but Authorization Zones do. The I-440 study region, however, was located in a safe airspace [76]. As a result, using drones is not subject to special authorization in either study area. However, the data gathering unit operated the drone using a Part 107 Airman Certificate issued by the FAA.

The characteristics of the study settings are examined for any features of man-made or organic items that can obstruct the line of sight. In neither case was there a major obstruction to the line of sight, which might have allowed for a minimum height of flight restriction. These study locations are examined for characteristics of man-made or natural items that may obstruct the line of sight. In neither case was there a major obstruction to the line of sight, which may allow for the specification of the minimum height of flight. Data was collected with the intention of capturing traffic conditions during heavy traffic. In order to accurately represent peak hour traffic and account for potential data

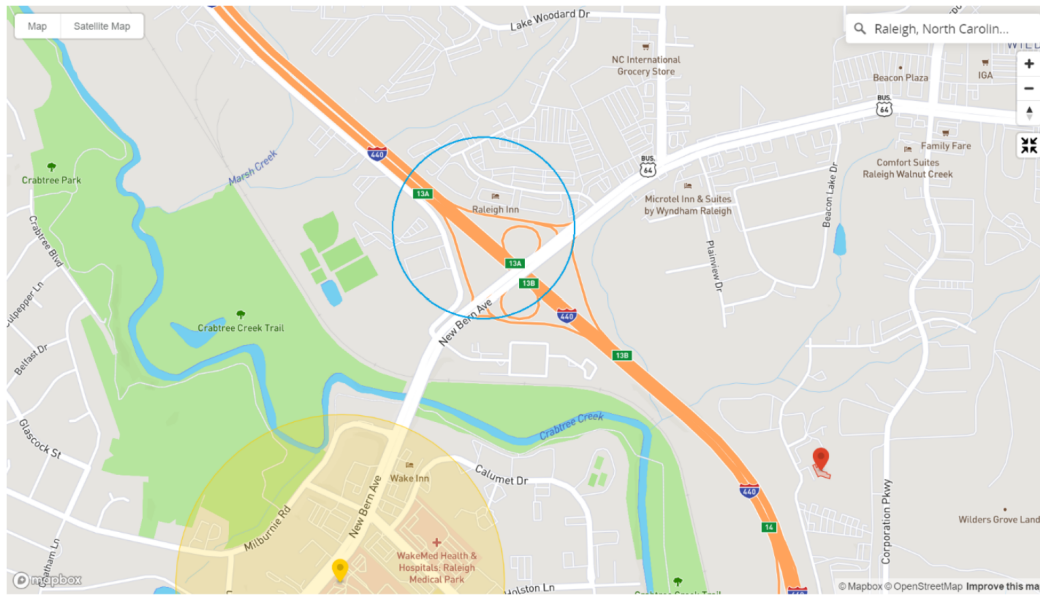


Figure 41. DJI's GEO System flying zone delineation for the I40 study area [76]

collecting errors, data was obtained repeatedly for about an hour. Thus, the information is gathered under two distinct flying states. The data was collected on I-440 on October 7, 2021, between 3 and 5 pm, during the PM peak. It was overcast outside. The drone was flying at a height of about 200 feet. The data footage lasted for almost 45 minutes. On I-40, however, data was gathered on September 23, 2021, between 4-6 pm, at the PM peak. It was a sunny and clear day. Between 140 and 200 feet above the ground, the drone was flown. In addition, the DJI Inspire 1 aircraft utilized in this investigation is outfitted with the Zenmuse X5 camera.

The open-source program DaVinci Resolve 17 is used for pre-processing the traffic stream video in order to stabilize the video frame and trim takeoff and landing footage. Georeferencing wasn't necessary for vehicle counting, though. The most common issue with I-40 video during data preprocessing was that it required extensive stabilization before being used in the background subtraction procedure. The primary cause was that the I-40's flight height was high enough to encompass moving trees and other aspects of the traffic stream, which had an impact on the effectiveness of the vehicle detecting algorithm. The crew tried to fix the problem by cropping part of the video frame because the footage was shot in 4K resolution. Unfortunately, the effort was less successful because the movement stabilization program was unable to handle the camera shaking on the portion of the video frame that was cut. The second problem related to the data gathering day and time's lighting. Strong shadows were created by the sunny, clear sky. These thick shadows contributed to more false alarm errors for the detection algorithm, lowering its effectiveness. These factors led to additional study of the video taken on I-40 being ignored.

It is proposed to use the OpenCV Library, an open-source library that contains a broad variety of efficient algorithms, to implement a two-block algorithm for auto-vehicle counting (Figure 42).

The program first recognizes moving cars in high-resolution video frames by subtracting the background using a Gaussian Mixture Model-based technique [287]. This technique determines which pixel intensities belong to the background by modeling each pixel's intensity using a Gaussian mixture model. Therefore, foreground is defined as any pixel intensity that does not match these values. The algorithm builds a mask by contrasting the current frame with a backdrop model. The resulting mask is a binary picture where the pixels from the moving item are removed from the current frame's backdrop model. The binary image is then followed by the drawing of contours, and finally bounding boxes are added on top of the contours. The positions of the bounding boxes are tracked in the subsequent block to see if they correspond to objects that were already picked up in the preceding frame. These objects are given distinctive IDs that correspond to the number of vehicles. Model Outcome At the initial run, the automatic vehicle counting algorithm had erroneous detection and missed detection. The algorithm effectively counted automobiles after making several adjustments. The difficulties and fine-tuning of the suggested model are explored below. As was noted in the data processing section, the background subtraction is the foundation for the proposed model's vehicle detector block. In order to function at their best, background subtraction algorithms often need a steady or immobile camera installation, a still background, and just enough illumination to avoid casting large shadows. These requirements are

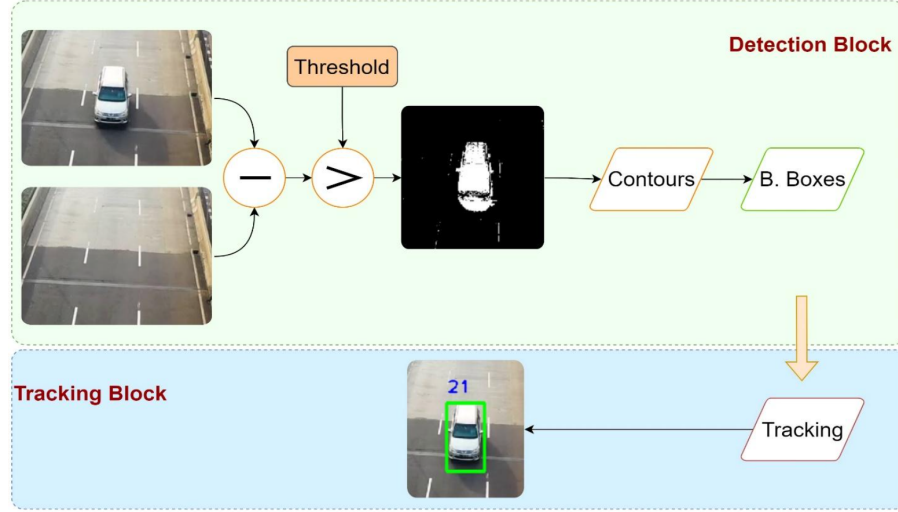


Figure 42. Auto-vehicle counting algorithm schematics

not always simple to meet because even while the drone is in hovering flying mode, the camera may eventually vibrate from wind gusts or motor vibration. Additionally, the weather may change suddenly. However, the team discovered from these criteria that careful planning for data gathering might greatly enhance model performance. This involves arranging the drone to reduce the impact of shadows by lining up the line of sight with the direction of the sun. Additionally, picking the proper flight altitude is crucial. The drone's flight height needs to be both high enough for safe operation and low enough to avoid adding too much dynamic background to the picture being captured. After several changes, the vehicle counting model achieved performance that was acceptable. The main adjustments involve choosing the appropriate input preprocessing and carefully defining the region of interest. Due to superior illumination and consistent frames, the data from I440 was appropriate for the model. Moreover, by modifying the detector's threshold value and expanding the region of interest to completely encompass such automobiles, false-positive values resulting from long vehicles, trucks, and track-trailers were greatly reduced. The accuracy, recall, precision, and F measure [257] [102] [258] [326]. In this study, Accuracy is used to assess the discrepancy between the counted value and the true value, Recall gauges a method's effectiveness (the ratio between relevant detection of the object of interest), Precision calculates the percentage of relevant detected objects in all detections, and the F-measure displays weighted harmonic average of Recall and Precision. The three measures are mathematically described here.

$$TrueNo. = TP + FN$$

$$CountedNo. = TP + FP$$

Where the Counted No. is the number of vehicles counted by the model and True No. is the actual number of autos passing a counting point in a given amount of time. The TP (True Positive) indicates the model's accurate detection of cars, the FN (False Negative) shows the model's inaccurate failure to detect vehicles, and the FP (False Positive) represents the model's inaccurate positive detection.

$$A = 1 - (CountedNo. - TrueNo.) / (TrueNo.)$$

$$P = TP / (TP + FP)$$

$$R = TP / (TP + FN)$$

$$F = 2 * (R * P) / (R + P)$$

Table 16. The performance of the proposed model

Model Performance Measure	'Well-stabilized' test data	Unstabilized sample test data
Precision	95.45%	58.33%
Recall	95.45%	100%
F-measure	95.45%	73.68%

Where, A is the model accuracy, P is the model precision, R is the recall, and F is the F-measure. The algorithm for the data from the I440 performance score are presented in Table 16. Table 2. Model performance measure

According to Table 16, the proposed model has an accuracy rating of almost 95 percent. The false-positive numbers from trucks that are counted more than once and the unsteady background were totally responsible for the 5 percent accuracy loss. As a result, the model's output demonstrates how sensitive the background subtraction-based detector is to the caliber of the input data and the degree of preprocessing. Moreover, unstabilized sample test data was used, and it result in substantial accuracy degradation, F1 score of 74 percent. This shows that the method adopted herein is more suitable for fix camera installation, and if need to be adopted for UAV data processing, the footage recording should be stable enough to generate reasonable performance.

4.5.3 Conclusion: The workload is made easier by the traffic research utilizing UAVs, which also offers several benefits. The capacity of UAVs to collect richer data, which is not achievable without the use of these platforms, can aid traffic engineers. Near real-time traffic parameter observation, less time and effort spent on data correction, top-down vision, and more detailed data when compared to conventional approaches are some of the main benefits of the UAV data gathering platform. Additionally, the data from UAVs is thought to be objective and is easily applicable for in-depth investigations like research on driver behavior. The basic procedures for a UAV-based traffic research are described in this article. The processes outlined in the procedures include the variables that must be taken into account during the planning, execution, and data processing stages, as well as how they affect the ensuing actions and decision-making. The framework is also used in planning, execution, and automated data processing to show how well the techniques suggested in this literature function. Future research may focus on expanding the spectrum of applications for UAVs for surveillance and reducing the quantitative resource consumption in traffic studies.

4.6 Task 5: Field experiments and testing

The milestones defined for the field deployment of the CAV testbeds included bringing up the sensors, GPS localization, map creation, lidar localization, human-machine interface, and cloud-based vehicle monitoring, wrapping up all the developments to demonstrate a last-mile transportation use case in the Gateway Research Park, a test track located in the north campus area of NC A&T.

In Figure 43a the sensors installed in the CAV testbeds (Polaris GEM e6) are shown, consisting of one radar Delphi ESR on the frontal bumper, two cameras of 3.2 MP with 12 mm and 16 mm of focal length, and one lidar VLP 32c of 200m of range and 30 degrees of field of view. These sensors are mainly employed for Object and Event Detection and Response (OEDR) focusing on redundancy as the sensor coverage are overlapped in front of the CAV testbeds as can be seen in Figure 43b. Essential work related to the extrinsic (sensors mountings improvements) and intrinsic (relating cameras and lidar positions) calibration of lidars and cameras was necessary, as well as the creation of calibration protocols to achieve the best performance of each testbed, as they share the same software stack to perform the autonomous driving mode.

In Figure 44 the GPS localization performance in the north campus test track is depicted. This kind of technology is often used for waypoint creation which is later employed for trajectory tracking. A poor localization performance due to tree tunnels (which is a common issue in rural areas) spikes the standard deviation error of the positioning estimation (for instances above 200 m) as depicted in Figure 44a, therefore. An Extended Kalman Filter has been employed to improve the performance, however, the lack of accuracy during long periods of time highly affects the waypoint creation which offers an unfeasible path to follow as shown in Figure 44b.

To overcome the issues of GPS localization, lidar localization has been implemented. It takes advantage of a

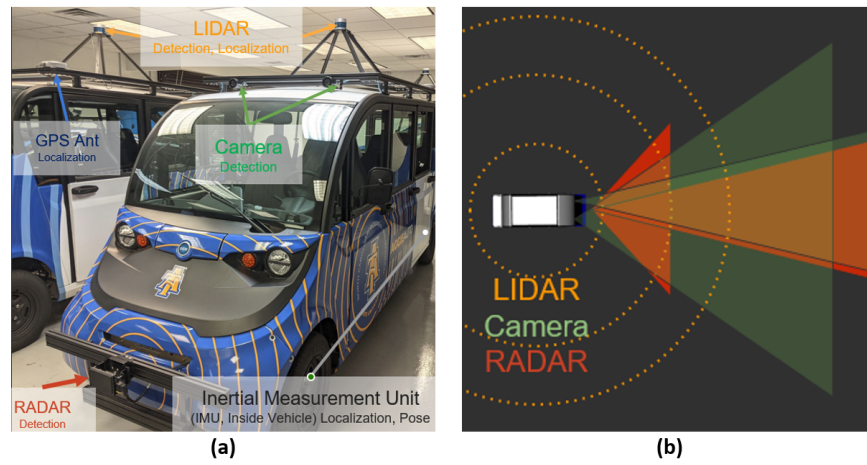


Figure 43. (a) Location of sensors installed on the CAV testbeds and their (b) safety cocoon

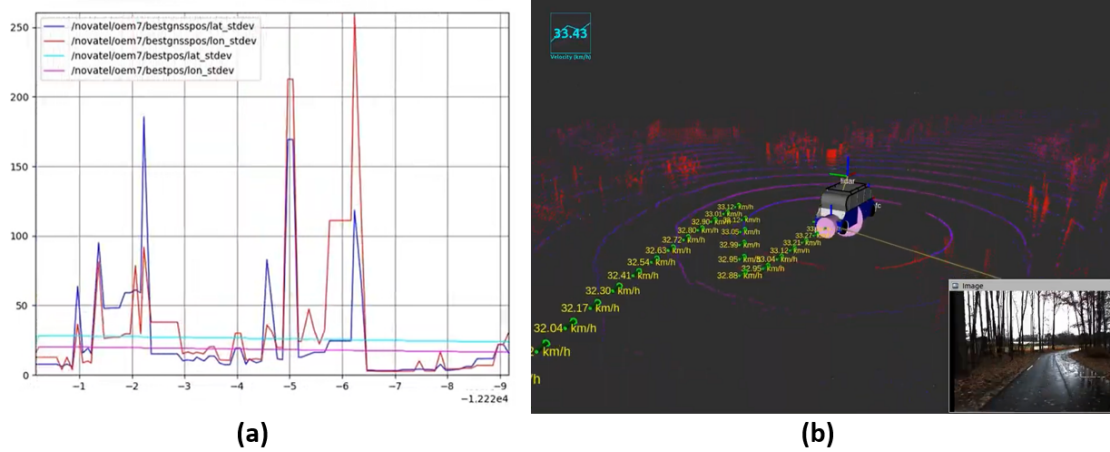


Figure 44. (a) standard deviation errors and (b) waypoint localization using GPS localization

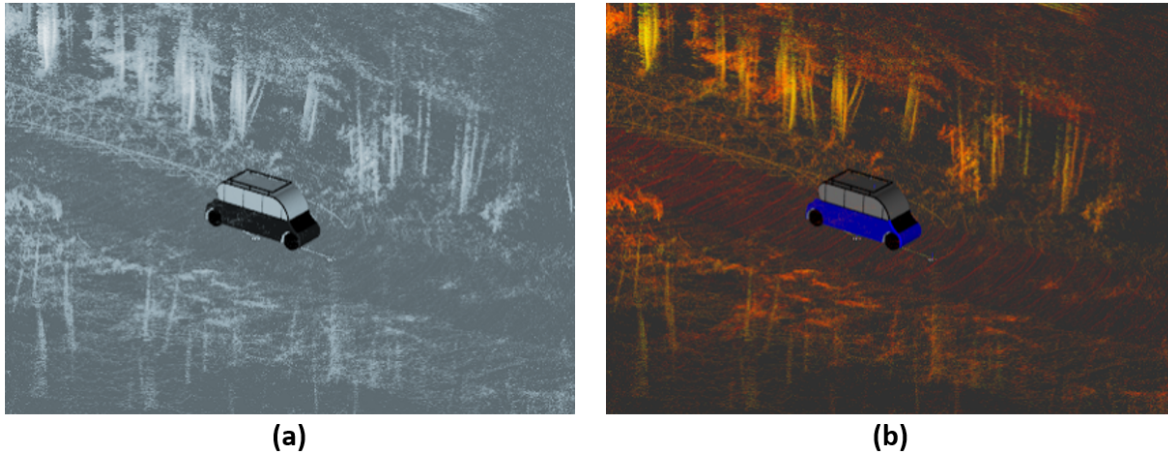


Figure 45. (a) subsection of global map and (b) what the lidar currently perceives
 Point Cloud Distribution (PCD) map created in advance from the area of interest, as well as a semantic map (lanelet2 map) which associates regulatory elements with the PCD map such as traffic lights, speed limits, stop signs, lane width, etc. The PCD map is obtained from recording data over the entire route or Operational Design Domain (ODD), consequently, an algorithm matches the PCD map with what the lidar on the car currently perceives for localization, as depicted in Figure 45, creating local pose (X, Y, Z) and orientation (roll, pitch, yaw) variables. The lanelet2 map is a time-intensive procedure performed by hand and is useful for trajectory planning algorithms.

The human-machine interface of the vehicle was implemented employing the “El Gato” StreamDeck device, used to automate basic tasks through sending command lines as a text interface with the automated driving system including the launching of systems, setting destinations, and setting the autonomous or manual mode.

Cloud-based vehicle monitoring covers the location pose tracking such as GPS location, heading, speed, etc., of each vehicle which sends their pose to a cloud-based database. This way, the monitoring interface pulls the latest pose data from the database for visualization. It is expected to expand the cloud database for additional monitoring data including battery level or sensor data, enable communications from the control room to vehicles, add user booking/request options, a mobile-friendly interface, and coordinate vehicles for optimum operation.

Chapter 5 Outreach, Dissemination, and Workforce Development Activities under NC-CAV Center

5.1 Outreach and Workforce Development Activities under NC-CAV Center

NC-CAV Center promotes a diverse, productive, and better-prepared workforce by involving graduate and undergraduate student, particularly those from underrepresented groups, across the three participating institutions in the research activities and exposing them to the advanced CAV transportation technologies.

- A website was established for the NC-CAV Center as a platform to share the research outcome with the public which is available at <https://www.nccav.com>
- A booklet was designed and prepared to share with the steering committee as well as public audience about NC-CAV scope of work and achievements. The booklet is available at <https://online.fliphtml5.com/gdoly/kryn>.
- **Developed Graduate and undergraduate Certificates in Autonomy:** NC-CAV researchers at NCAT contributed to the development of an Autonomy Certificate at NC AT graduate and undergraduate programs and passed it through for approvals from the Electrical and Computer Engineering Department (the lead department), and the other relevant departments including Computer Science, Mechanical Engineering, Industrial and Systems Engineering, and Computational Science Engineering Departments, as well as, the College of Engineering. The Graduate Certificate in Autonomy has 3 tracks including:
 - **Track 1:** Smart Transportation and Autonomous Vehicles
 - **Track 2:** Intelligent Control Systems
 - **Track 3:** Smart Power and Energy Systems
 - **Track 4:** Cyber Physical Systems

The Undergraduate Certificate in Autonomy has 4 tracks

- **Track 1:** Smart Transportation and Autonomous Vehicles
- **Track 2:** Track Smart Manufacturing and Automation
- **Track 3:** Unmanned Aerial Vehicles

Electrical and Computer Engineering at NCA&T led these certificate programs supported by several other departments including Computer Science, Mechanical Engineering, Industrial and Systems Engineering, and Computational Science Engineering.

- **Joined the “IT! It is for Girls” Summer Camp:** As part of our outreach, dissemination and workforce development activities, the NC-CAV Center team joined the “IT! is for Girls” summer camp in collaboration with the American Association of University Women (AAUW) with the objective of inspiring young girls to pursue interests in STEM education and transportation technologies in the future. During the one-week summer camp the middle school girls explored subjects and got to do hands-on projects on Internet of Things, robotics, and coding using Alice 2.0. Hosted by NC-CAV Center and Autonomous Cooperative Control of Emergent Systems of Systems (ACCESS) lab at NC A&T, Dr. Ali Karimoddini and Dr. Leila Hashemi provided a lab tour to the students. and educated the participants about the current research activities and research objectives of the NC-CAV Center. The breakout sessions were led by the graduate students who answered the questions of the girls during the breakout sessions with the objective to attract their interest into STEM education and transportation technologies in the future.
- **Presented at Vision Zero Summit 2020:** Vision Zero Greensboro (VZGSO) hosted the second annual summit on February 13, 2020 at Barber Park Event Center to update stakeholders on the status of the program and re-engage them to move into the implementation stage. Dr. Karimoddini from the NC-CAV Center attended this event and gave a talk about *How Technology Can Contribute to Vision Zero?* to highlight the role of Autonomy and potential impacts of Autonomous Vehicles on improving the safety of transportation systems and in particular vulnerable road users such as pedestrians and bicyclists.

- **Organized workshops on RTI Connex DDS Secure:** NC-CAV and RTI organized two workshops on RTI Software Framework. The first workshop on Jan 20, 2021, provided the attendees with the introductory training including the basic functionality of Connex DDS as well as the best practices to use the rich set of RTI tools efficiently. The Connex DDS RTI involves the implementation of application logic, message filtering, caching and persistence, addressing, node and service discovery, Quality of Service, serialization/Marshaling, reliability, encryption and authorization, socket programming, and network stack, which all are needed for reliable communication between CAVs' components. RTI Connex Drive uses the Next Generation of EE architectures for autonomous driving where DDS serves to manage some amount of involved complexity at its own as it can offer integration of many different dataflows of different volumes, frequencies, latencies, reliability and destinations and multiple hardware and software solutions. DDS is a software defined radio that uses the underlying IP network to make the communication as distributed and offers application-based customizing where the user can prioritize the involved parameters to establish a customized QoS with the availability of a default and recommended QoS setting.

The second workshop on February 23, 2021, was about the integration of Connex DDS and ROS. RTI works on the mapping layer for Robot Operating Systems (ROS) and the user may have some ROS2 nodes with DDS to enable seamless communication between ROS2 and DDS. RTI can use this methodology to bridge between different technologies to provide safety certifications.

- **Supported the Aggies Autonomous Auto (A3) team in the Autodrive Challenge:** A team from the College of Engineering at N.C. A&T, the Aggies Autonomous Auto (A3) team attended the Autodrive Challenge. Organized by SAE International and General Motors, the Autodrive Challenge is a four-year competition to develop and demonstrate a fully autonomous passenger vehicles.

The technical goal of the competition is to navigate an urban driving course in an automated driving mode as described by SAE Standard (J3016) level 4 definition by year three. Through this competition, GM provided N.C. A&T team with a Chevrolet Bolt EV as the vehicle platform. Strategic partners and suppliers such as Intel provided the team with the vehicle parts and software.

Year 4 (2021) was the last year of this inaugural series of the AutoDrive Challenge™ competition was held in June 2021 in Ann Arbor, Michigan. The Year 4 focused on proof-of-concept demonstration drive according to the SAE Standard (J3016) Level 4. From the NC-CAV Center, Drs. Karimoddini, Hashemi Beni, John Kelly, and Homaifar supported the NCA&T Autdrive team in different capacities such as serving as the faculty advisor or providing funding to attend this competition.

- **Supported a senior design team which was placed first in the College of Engineering Competition in 2020:** A senior design group, partially supported by NC-CAV Center designed a Package Delivery Drone concept. The group consisted of Nabeel Abdelmajid, Kristofer Bailey, William Hall, and Brianna Patterson.

The group was placed first in the 2020 Senior Design Competition, in NCA&T College of Engineering.

- **Organizing a special session on CAVs in IEEE SMC 2021 Conference:** Drs. Ali Karimoddini and Abdollah Homaifar (North Carolina AT State University, USA) and Dr. Shih-Chun Lin (North Carolina State University) organized a special session on "Connected and Autonomous Vehicles" in IEEE International Conference on Systems, Man, and Cybernetics, on 17-20 October, 2021. This special session was focusing on the state of the art and practice solutions for addressing key challenges that exist in developing and operationalizing CAVs, including efficient computer vision algorithms for AV perception systems, communication backbone for CAVs' connectivity, traffic volume prediction techniques, and state of the practice testbeds for connected autonomous vehicle testbeds, as well as CAV applications.
- **Briefing NCDOT Board of Transportation:** The NC-CAV team attended the Advanced Technology Board meeting and briefed the NCDOT Board of Transportation on April 7, 2021, and presented the NC-CAV activities and progress.
- **Organizing a workshop at IEEE ITSC 2021 Conference:** NCCAC researchers along with researchers from Indiana University Purdue University Indianapolis, Toyota Motor North America, and Huawei Technologies Canada, organized the 1st Workshop on the Detection, Recognition, and Prediction of Pedestrian Behaviors in 24th IEEE International Conference on Intelligent Transportation - ITSC2021, on September 19, 2021. The workshop materials are available at <https://itsc2021.github.io/WPB/>. This Workshop was focusing on

the detection, recognition, and prediction of pedestrian behaviors. The goal was to build a platform for sharing state-of-the-art models, algorithms, and datasets in the field and identifying research needs and directions. The following topics were covered in this workshop:

- Pedestrian detection and tracking
 - Pedestrian trajectory prediction
 - Pedestrian intention estimation
 - Pedestrian behavior and action recognition
 - Pedestrian behavior modeling
 - Factors affecting pedestrian behavior and decision-making
 - Vehicle-pedestrian interaction
 - Vehicle decision-making
- **Participated in NCDOT Research and Innovation Summit:** NC-CAV team provided an update on each of the projects at NC-CAV Center in NCDOT Research and Innovation Summits in 2021-2023.
 - **Co-organizing the Virtual Summer Camp for High School Students:** NC-CAV Center joined the transportation Institute at NC A&T to organize a Virtual Summer Camp for High School students on July 15, 2021. NC-CAV Center contributed to this program by organizing a workshop on CAV technologies and their roles in future transportation systems. Dr. Mubbashar Altaf Khan, the post-doctoral research associate for the NC-CAV Center presented the high school students with some of the interesting research being conducted under the NC-CAV Center to develop their interest in pursuing STEM studies.

5.1.1 NC-CAV: Sustainability Activities: The NC-CAV research team has been exploring the potential funding opportunities to sustain the Center activities around the concept of CAVs in the future. The NC-CAV team has been exploring different opportunities under DOT, DOE, and NSF programs to sustain the Center activities around the concept of CAVs.

- **Regional Transportation Center, DOT, \$15M:** A research team led by NA&T, was awarded by DOT for \$15 M in 2023 to establish a Center for Regional and Rural Connected Communities (CR^2C^2). The CR^2C^2 will serve as the Region 4 (Southeast) University Transportation Center (UTC) charged with addressing transportation challenges within the southeastern region of the United States. This region includes Alabama, Florida, Georgia, Kentucky, Mississippi, North Carolina, Puerto Rico, South Carolina, and Tennessee. The primary goal of CR^2C^2 is to plan, implement, and evaluate an integrated research, education, workforce development, and technology transfer approach for providing innovative connected and coordinated multimodal technological solutions to enable and improve equitable, efficient, and effective mobility services for the movement of people and goods primarily, but not exclusively, in rural and underserved communities.
- **Developing a Testbed of Connected Autonomous MicroTransit Vehicles, NSF, \$785,000:** A team of researchers from NC-CAV Center received \$550k from NSF and \$235k from NCDOT, Downtown Greensboro Inc., and NCA&T College of Engineering to establish a network of self-driving shuttles. In this project, the research team will develop a CAV testbed consisting of three self-driving shuttles, along with the required sensing and communication networks. This advanced transportation testbed enables fundamental research in the development, deployment, and validation of Connected Autonomous Vehicle (CAV) technologies and will be developed and tested at a one-mile test track at the NCA&T North Campus Gateway Research Park. This research infrastructure will enable partnerships between regional and national collaborators in academia, industry and at national labs in order to advance networks of autonomous vehicles. The research team is led by Karimoddini and he will collaborate with COE colleagues Abdullah Eroglu, Ph.D., Balakrishna Gokaraju, Ph.D., Abdollah Homaifar, Ph.D., Steven Jiang, Ph.D., John Kelly, Ph.D., Daniel Limbrick, Ph.D., Mahmoud Mahmoud, Ph.D., and Ioannis Raptis, Ph.D. Additional researchers include College of Science and Technology faculty members Leila Hashemi Beni, Ph.D., and Evelyn Sowell, Ph.D., and Willie A. Deese College of Business faculty member Maranda McBride, Ph.D.

- **Excellence in Research: Real-time Fault Diagnosis for Self-Driving Vehicles, NSF, \$1M:** A team of researchers from NC-CAV Center was awarded by NSF for \$1M to develop Real-time Fault Diagnosis for Self-Driving Vehicles. This research will facilitate the development of in-the-field error mitigation techniques, resulting in more reliable autonomous cars. Multi-perspective error detection techniques, including discrete-event system analysis, data-driven analysis, and chip-level analysis, will be combined to diagnose faults in automotive systems.
- **University Leadership Initiative (ULI): Secure and Safe Assured Autonomy, NASA, \$8M:** A team of researchers from NC-CAV Center was awarded by NASA for a 4-year \$8M ULI grant to develop Safe and Secure Assured Autonomy for Advanced Air Mobility (AAM) systems including Urban Air Mobility (UAM) vehicles, cargo and special mission aircraft into the National Airspace System (NAS). These developments leverage technologies in autonomy, UAS Traffic Management (UTM), electric powertrain reliability, multi-redundant flight systems architectures, and advancing wireless connectivity, to enable unique requirements of AAM airspace and aircraft management. Funded by NASA's Aeronautics University Leadership Initiative (ULI), our team is advancing the industrial deployment of secure and safe assured autonomy to meet the following needs (1) Manage air traffic in dynamic and uncertain airspace operations, (2) Operate securely and safely in varying levels of system complexity. From the NC-CAV Center, Dr. Homaifar will be leading this new ULI program and Dr. Karimoddini will be leading the Technical Challenge 1 on Safe Perception, Coordination, Planning, and Navigation to develop flexible and adaptive coordination and control algorithms for Urban Air Mobility (UAM).
- **Robust and Resilient Autonomy for Advanced Air Mobility:** A team of researchers from NC-CAV Center joined researchers from University of Illinois, Urbana-Champaign, Georgia Tech, Massachusetts Institute of Technology, North Carolina AT State University, University of Nevada at Reno, Lockheed Martin, and Sierra Nevada Corporation to develop "Robust Resilient Autonomy for Advanced Air Mobility." More specifically, the team will deliver trustworthy autonomy tools to help Advanced Air Mobility aircraft fly safely through complex airspace, typical of dense urban environments. The award was received from NASA for \$6M over 3 years starting from Aug 2022.
- **Improving the performance and runtime efficiency of the object detection and classification, Ford Motors, \$100k:** A team of researchers from NC-CAV received \$200k from Ford Motors over 2 years starting from Jan 2022 to improve the performance and runtime efficiency of the object classifiers for detecting, tracking, and modeling of pedestrians as well as traffic signs/lights etc. More specifically, the team will (1) explore fusing different networks and inferences with manageable runtime overhead through parallel fusion mechanisms, and (2) explore the implementation of the developed networks on the RPI4B+, NVIDIA Jetson by achieving an optimized speed in network communication using edge computing, while maintaining IoT devices.
- **Developing and Operationalizing a Testbed of Connected Self-driving Shuttles to Test and Develop CAV Applications in North Carolina, NCDOT, \$290k:** A team of researchers from NC-CAV received \$290k from NCDOT to develop and operationalize a flexible and customizable open hardware/software testbed for connected autonomous micro transit vehicles. This will be achieved by developing and operationalizing a CAV testbed of self-driving shuttles through the following objectives: (1) Installing, testing, and operationalizing the hardware components of the CAV testbed, in which all hardware components are modifiable according to the application in mind, (2) Developing and testing software components of the CAV testbed, (3) Installing, testing, and operationalizing the communication devices of the CAV testbed with the capability of communicating with other vehicles and infrastructure which follow SAE and IEEE standards for CAVs, (4) Integration of the components of the developed CAV testbed, (5) Implementation and deployment of the CAV testbed, (6) Development and offering workshops on the develop technology in order to safely give access to transportation researchers in NC to use the developed CAV testbed.
- **Aggie Autonomous Auto- SAE AutoDrive Challenge II:** Followed by successful performance of NCA&T team in Autodrive Challenge I, a team of researchers from NCA&T received \$129k from SAE International and

Chevy Bolt EV from GM to attend the Autodrive II challenge. The goal of this project is to develop advanced control, perception, and navigation tools to convert it into a level-4 autonomous car.

5.1.2 NC-CAV Center Activities for the Engagement of Stakeholders and Industrial Partners

- **Collaboration with NCDOT:** The research team at NC-CAV were collaborating with NCDOT staffs to ensure that NC-CAV outcomes will be aligned with the NCDOT vision. The purpose of the meetings were to seek NCDOT's input and guidance on the case studies and discuss possible choices of engagement, opportunities for early feedback, and technology transfer.
- **Collaboration with City of Greensboro:** NC-CAV Center started collaboration with City of Greensboro Department of Transportation and Downtown Greensboro Inc. to explore opportunities for improving access and mobility to and through Downtown by using self-driving shuttles being developed under NC-CAV Center. Pilot programs and phasing approaches were discussed for testing and adapting shuttle routes were discussed to maximize efficiency, accommodate major events, and serve new destinations. In a route that connects the East-West connections between UNC Greensboro, Downtown, and North Carolina A&T was selected as a candidate route for self-driving shuttles.
As stated in the DOWNTOWN GREENSBORO 2030 STRATEGIC VISION, dedicated traffic lanes will be considered for autonomous vehicles (AVs) and self-driving shuttles in the first phase. It is envisioned that shuttles can easily change routes and adapt over time. NC-CAV Center will contribute to this plan by employing emerging technology for autonomous vehicles to provide on-demand mobility services using self-driving shuttles.
- **Partnership with Verizon:** The NC-CAV team communicated with Verizon Wireless for their engagement into the NC-CAV Center activities. Several meetings were organized to discuss the needs, collaboration opportunities, and the way that Verizon can support the Center. An NDA agreement was signed, and communication is being continued to have them an official sponsor of the project by:
 - Providing the technical support needed under Thrust 2 of the NC-CAV Center to investigate the communication needs for future CAVs.
 - Providing the technical support and communication devices needed for the development of a CAV testbed. As the first step, it was agreed that Verizon will be providing the communication devices to set up a ground station (control room) and a mobile station (a car) to set up the system to train NC-CAV researchers and to identify the 5G network coverage around a candidate route.

Discussions between the NC-CAV Center team and Verizon Wireless were continued during 2021-2022. Verizon wireless provided the NC-CAV team with three M2100 demo devices to establish the 5G communication between mobile nodes. These devices will enable the communication between the autonomous cars and the infrastructure will eventually lead to the development of the CAV testbed for its deployment on the proposed route. Follow-up meetings were held with the Verizon team after evaluating the pros and cons of the M2100 with respect to their feasibility to be used for the establishment of the communication that is required for the deployment of CAVs. The team has developed a virtual private network (VPN) using the 4G communication initially and will be implementing the same process to establish the VPN using 5G services to enable the communication using M2100 devices. The NC-CAV team has evaluated another device, namely, S2000, that is available with Verizon Wireless that can enable 5G communication between mobile nodes and offers features that more closely match the requirements for establishing the communication needed between CAVs to prepare the CAV-testbed for the project. The NC-CAV researchers are in communication with Verizon Wireless to provide the S2000 demo devices that can be tested for the purpose of establishing the communication for the CAV testbed.

- **Partnership with RTI:** NC-CAV and Real-Time Innovations (RTI) started collaboration on reliable communication for Connected Autonomous Vehicle testbed. RTI is a leading Software Framework Provider for Smart Machines and Real-World Systems with Connex as leading product, which provides DDS as an application for Internet of Things (IoT) that enables implementation of distributed network applications.
RTI has provided the NC-CAV team with Connex DDS software, which can be used as a middleware for developing the NC-CAV use cases to increase the reliability and communication efficiency. RTI provided

NC-CAV team with training workshops introducing the basic functionality of Connex DDS and providing focused guidance and best practices to help the NC-CAV researchers to get started and to integrate Connex DDS and ROS. RTI also agreed to help the researchers in understanding how to use the rich set of RTI tools efficiently.

- **Partnership with Siemens:** Siemens sponsored the NC-CAV Center by providing the software products including TASS MADYMO and TASS PreScan. The conversation is going on with Siemens to make Aimsun available to the NC-CAV researchers as well.

MADYMO simulator contains human model portfolio comprises both passive and active models a software suite for analyzing and optimizing occupant safety. PreScan simulation platform consists of a GUI-based preprocessor to define scenarios, model sensors, and control the AVs. Aimsun can be used for traffic planning, simulation and prediction allowing NC-CAV researchers to model anything from a single intersection to an entire region.

5.2 Dissemination of Research Findings

5.2.1 NC-CAV Seminar Series: The NC-CAV Seminar Series sessions started in September 2020 and continued on monthly basis throughout the duration of the project. The PIs, Graduate and undergraduate students from the campuses of the three participating universities and researchers from both academia and industry and NCDOT personnel joined these seminar series sessions in which the distinguished researchers working in the domain gave talks about the recent updates on the technologies and research methodologies being carried out for the development of Connected and Autonomous Vehicles. Recordings of the seminar series sessions are made available on the NC-CAV website (<https://www.nccav.com/seminars>) to the participants and public for future reference. Seminar sessions that were conducted throughout the duration of the project include:

1. **Title:** Anomaly Detection for Autonomous Driving
 - **Speaker:** Dr. Abdullah Al Redwan Newaz
 - **Link:** <https://www.nccav.com/seminars/2020-9-redwannewaz>
2. **Title:** Introduction to Connected Traffic Signals
 - **Speaker:** Mr. Thomas Chase
 - **Link:** <https://www.nccav.com/seminars/2020-10-thomaschase>
3. **Title:** North Carolina Transportation and Infrastructure Revenues in the Era of COVID-19 and Beyond
 - **Speaker:** Dr. Nicolas D. Norboge
 - **Link:** <https://www.nccav.com/seminars/2020-12-nicolas-d-norboge>
4. **Title:** Lane Detection for Autonomous Driving: Conventional and CNN approaches
 - **Speaker:** Dr. Tesfamichael Getahun
 - **Link:** <https://www.nccav.com/seminars/2021-1-tesfamichael>
5. **Title:** Public Perceptions of Transportation Fees and Taxes
 - **Speaker:** Dr. Daniel Findley
 - **Link:** <https://www.nccav.com/seminars/2021-2-danielfindley>
6. **Title:** Machine Learning-Enabled and Ultra-Low Latency Connected Transportation
 - **Speaker:** Dr. Shih-Chun Lin
 - **Link:** <https://www.nccav.com/seminars/2021-3-shih-chun-lin>
7. **Title:** Data-Centric Architecture: The foundation to CAV design and performance
 - **Speaker:** Mr. Bob Leigh
 - **Link:** <https://www.nccav.com/seminars/2021-4-bob-leigh>

8. **Title:** Mitigating Freeway Congestion at Bottlenecks through Variable Speed Limit Control in Connected Autonomous Vehicle Environment
 - **Speaker:** Dr. Wie Fan
 - **Link:** <https://www.nccav.com/seminars/2021-5-wie-fan>
9. **Title:** Traffic Control in the Era of Connected Automated Vehicles
 - **Speaker:** Dr. Ali Hajbabaie
 - **Link:** <https://www.nccav.com/seminars/2021-7-ali-hajbabaie>
10. **Title:** Mobile Mapping Systems for Accurate Documentation of Transportation Corridors
 - **Speaker:** Dr. Ayman Habib
 - **Link:** <https://www.nccav.com/seminars/2021-8-dr-ayman-habib>
11. **Title:** Impact of Automated, Connected, Electric, and Shared Vehicles on Transportation Revenue Collection
 - **Speaker:** Dr. Steven Jiang
 - **Link:** <https://www.nccav.com/seminars/2021-9-dr-steven-jiang>
12. **Title:** Toward Seamless Human-Automation Handovers - An Adaptive Haptic Shared Steering Control for Ground Vehicles
 - **Speaker:** Dr. Amirhossein Ghasemi
 - **Link:** <https://www.nccav.com/seminars/2021-10-dr-amirhossein-ghasemi>
13. **Title:** Implementing Solutions from Transportation Research and Evaluating Emerging Technologies (I-STREET)
 - **Speaker:** Dr. Pruthvi Manjunatha
 - **Link:** <https://www.nccav.com/seminars/2021-11-dr-pruthvi-manjunatha>
14. **Title:** Detecting ACC-Driven Vehicles in Vehicle Trajectory Data
 - **Speaker:** Dr. Alireza Talebpour
 - **Link:** <https://www.nccav.com/seminars/2021-12-dr-alireza-talebpour>
15. **Title:** Security and Resiliency of Cyber-Physical-Social Systems for Connected and Automated Transportation Systems
 - **Speaker:** Dr. Mashrur “Ronnie” Chowdhury
 - **Link:** <https://www.nccav.com/seminars/2022-1-dr-mashrur-ronnie-chowdhury>
16. **Title:** A Prospective Application of Artificial Intelligence in CAV Operations
 - **Speaker:** Dr. Samuel Labi and Dr. Sikai (Sky) Chen
 - **Link:** <https://www.nccav.com/seminars/2022-2-dr-samuel-labi-and-dr-sikai-sky-chen>
17. **Title:** Driving Autonomous Vehicles in Partial Observable Environments
 - **Speaker:** Dr. Abdullah Al Redwan Newaz
 - **Link:** <https://www.nccav.com/seminars/2022-3-dr-abdullah-al-redwan-newaz>
18. **Title:** Design of standard crash scenarios and testing for vehicle AEB systems
 - **Speaker:** Dr. Yaobin Chen
 - **Link:** <https://www.nccav.com/seminars/2022-4-dr-yaobin-chen>

19. **Title:** Optimization, Modeling and Assessment of Smart City Transportation Systems

- **Speaker:** Dr. Hesham A. Rakha
- **Link:** <https://www.nccav.com/seminars/2022-5-dr-hesham-rakha>

20. **Title:** Testing and Verifying the Security of Connected and Autonomous Vehicles

- **Speaker:** Dr. Arman Sargolzaei
- **Link:** <https://www.nccav.com/seminars/2022-9-dr-arman-sargolzaei>

21. **Title:** Deep learning approaches for pedestrian detection for enhancing safety of autonomous vehicles

- **Speaker:** Mr. Muhammad Mobaidul Islam
- **Link:** <https://www.nccav.com/seminars/2022-10-mr-muhammad-mobaidul-islam>

22. **Title:** Intersection Capacity Adjustments Considering Different Market Penetration Rates of Connected and Autonomous Vehicles

- **Speaker:** Dr. Li Song
- **Link:** <https://www.nccav.com/seminars/2022-11-dr-li-song>

23. **Title:** Next-Generation Wireless Networking Architecture for Vehicular Communications

- **Speaker:** Mr. Chia-Hung Lin
- **Link:** <https://www.nccav.com/seminars/2023-01-chia-hunglin>

24. **Title:** Running on Empty: CAV Revenue Challenges and Solutions for Vehicular Communications

- **Speaker:** Mr. Ryan Hassett
- **Link:** <https://www.nccav.com/seminars/2023-02-ryan-hassett>

5.3 Publications and Reports

Throughout the duration of the project, several publications and multiple reports and newsletters were published to make academic contributions to the developments in the Connected Autonomous Vehicle technology. Following is the list of those publications.

[1] Muhammad Mobaidul Islam, Abdullah Al Redwan Newaz, Balakrishna Gokaraju, and Ali Karimoddini, “Pedestrian detection for autonomous cars: Occlusion handling by classifying body parts,” In 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pages 1433–1438, IEEE, 2020.

[2] Md Ferdous Pervej and Shih-Chun Lin, “Eco-vehicular edge networks for connected transportation: A distributed multi-agent reinforcement learning approach,” In 2020 IEEE 92nd Vehicular Technology Conference (VTC2020-Fall), pages 1–7, 2020.

[3] Lin, Shih-Chun, Kwang-Cheng Chen, and Ali Karimoddini, “SDVEC: software-defined vehicular edge computing with ultra-low latency,” IEEE Communications Magazine 59.12 (2021): 66-72.

[4] Chen, Kwang-Cheng, et al, “Wireless networked multirobot systems in smart factories,” Proceedings of the IEEE 109.4 (2020): 468-494.

[5] Li Song, and Wei Fan, “CAV Impacts on Traffic Intersection Capacity. A report of findings of Project TCE2020-01, NC-CAV Center of Excellence on Connected and Autonomous Vehicles, Thrust 1: Impact of CAVs on North Carolina’s Transportation System and Associated Revenue,” Available at: <https://www.nccav.com/resources/reports/litsurveyimpactintersectioncapacity>.

[6] Morgan Crowder, Steven Jiang, James Poslusny, Nicolas Norboge, Steve Bert, and Daniel Findley, “Impacts

of Automated, Connected, Electric, and Shared Vehicles on Transportation Revenue Collection. A report of findings of Project TCE2020-02, NC-CAV Center of Excellence on Connected and Autonomous Vehicles, Thrust 1: Impact of CAVs on North Carolina's Transportation System and Associated Revenue," Available at: <https://www.nccav.com/resources/reports/litsurveyimpacttransportationrevenue>.

[7] R. Thomas Chase, Guangchuan Yang, Ishtiak Ahmed, Shoaib Samandar, Shih-Chun Lin, Chia-Hung Lin, Chien-Yuan Wang, John Kelly, and Mansi Bhavsar, "Impacts of connected and autonomous vehicles on traditional and emerging transportation infrastructure." A report of findings of Project TCE2020-02, NC-CAV Center of Excellence on Connected and Autonomous Vehicles, Thrust 2: Impacts of Connected and Autonomous Vehicles on Traditional and Emerging Transportation Infrastructure," 06-01-2021, Available at: <https://www.nccav.com/resources/reports/litsurveyimpacts-of-connected-and-autonomous-vehicles-on-traditional-and-em>

[8] Chia-Hung Lin, Shih-Chun Lin, Chien-Yuan Wang, and Thomas Chase, "A c-v2x platform using transportation data and spectrum-aware sidelink access," In 2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pages 1293–1298, IEEE, 2021.

[9] Tesfamichael Getahun, Ali Karimoddini, and Priyantha Mudalige, "A deep learning approach for lane detection," In 2021 IEEE International Intelligent Transportation Systems Conference (ITSC), pages 1527–1532, 2021.

[10] Benjamin Lartey, Abdollah Homaifar, Abenezer Girma, Ali Karimoddini, and Daniel Opoku, "Xgboost: a tree-based approach for traffic volume prediction," In 2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pages 1280–1286, IEEE, 2021.

[11] Muhammad Mobaidul Islam, Abdullah Al Redwan Newaz, and Ali Karimoddini, "A pedestrian detection and tracking framework for autonomous cars: Efficient fusion of camera and lidar data," In 2021 IEEE International Conference on Systems, Man, and Cybernetics (SMC), pages 1287–1292. IEEE, 2021.

[12] Muhammad Mobaidul Islam, Abdullah Al Redwan Newaz, Renran Tian, Abdollah Homaifar, and Ali Karimoddini, "A computationally effective pedestrian detection using constrained fusion with body parts for autonomous driving," In 2021 Fifth IEEE International Conference on Robotic Computing (IRC), pages 106–110, IEEE, 2021.

[13] Lin, Chia-Hung, Shih-Chun Lin, and Erik Blasch, "Tulvcan: Terahertz ultra-broadband learning vehicular channel-aware networking," IEEE INFOCOM 2021-IEEE Conference on Computer Communications Workshops (INFOCOM WKSHPS). IEEE, 2021.

[14] Lartey, Benjamin, et al, "A Data-driven Approach for Travel Time Prediction and Analysis," 2022 IEEE International Conference on Systems, Man, and Cybernetics (SMC). IEEE, 2022.

[15] Islam, Muhammad Mobaidul, and Ali Karimoddini, "Pedestrian Detection for Autonomous Cars: Inference Fusion of Deep Neural Networks," IEEE Transactions on Intelligent Transportation Systems 23.12 (2022): 23358-23368.

[16] Muhammad Mobaidul Islam, Abdullah Al Redwan Newaz, Li Song, Benjamin Lartey, Shih-Chun Lin, Wei Fan, Ali Hajbabaie, Mubbashar A. Khan, Thomas Chase, Alireza Partovi, Abdollah Homaifar, and Ali Karimoddini, "Connected Autonomous Vehicles: State of Practice," Submitted for publication, 2022.

[17] Li Song, Wei Fan, "Intersection capacity adjustments considering different market penetration rates of connected and automated vehicles," submitted for publication, 2023.

[18] North Carolina Transportation Center of Excellence on Connected and Autonomous Vehicle Technology (NC-CAV) newsletter, issue 2021," Available at: <https://online.fliphtml5.com/jkjxu/hgpn/?1615675920316#p=1>

[19] *North Carolina Transportation Center of Excellence on Connected and Autonomous Vehicle Technology (NC-CAV) newsletter, issue 2022,”*
Available at: <https://online.fliphtml5.com/jkjxu/vvxn/?1649384638159#p=1>.

Chapter 6 Conclusions

The North Carolina Transportation Center of Excellence on Connected and Autonomous Vehicle Technology (NC-CAV), founded in 2019 under the contract TCE2020-03, brought together a strong and diverse team of researchers from North Carolina A&T State University (NCA&T), North Carolina State University (NCSU), and University of North Carolina at Charlotte (UNCC) with the goal of establishing a multidisciplinary Center of Excellence in “Advanced Transportation Technologies” to investigate the adoption, utilization, and deployment of CAVs and their impacts on the transportation system in North Carolina and the nation. Toward this goal, NC-CAV Center achieved the following:

- NC-CAV researchers created a new dimension of research foundation and infrastructure in North Carolina in terms of Connected Autonomous Vehicles as emerging transportation technology which helps NCDOT to understand (1) the impact of CAVs on traffic flow and the revenue impact of adopting CAVs, (2) the required infrastructure for to facilitate the deployment and adoption of CAVs into North Carolina transportation systems, and (3) developed early prototypes of CAV testbeds and simulator that can support implementation of CAV pilot programs and use case application of CAVs.
- NC-CAV leveraged the provided funding by NCDOT to develop the Center into a national forum for CAV research, which is evident from the monthly seminars, the impactful publications, the reports, and the organized workshops and special sessions at national and international levels.
 - See NC-CAV seminars: <https://www.nccav.com/seminars>
 - See NC-CAV publications: <https://www.nccav.com/resources/publications>
 - See NC-CAV newsletters: <https://www.nccav.com/resources/newsletters>
 - See NC-CAV reports: <https://www.nccav.com/resources/reports>
- The NC-CAV Center leveraged the provided funding by NCDOT to enhance partnership with other agencies, industrial partners, and local community, which include:
 - Partnered with Verizon, Ford, RTI, and Siemens to support NC-CAV research on AV development efforts and the V2X communication aspects,
 - Partnered with City of Greensboro and Downtown Greensboro Inc. to explore the feasibility of using autonomous shuttles between NCAT and downtown Greensboro,
 - Secured large funding from DOT, NASA, and NSF on researching safety of AVs and UAVs,
 - Established the nation’s first AV rural track and a fleet of Autonomous shuttles. Leaders in local, state and federal transportation including Federal Highway Administration chief Stephanie Pollack, Greensboro Mayor Nancy Vaughan joined us to unveil the new infrastructure and to “test ride” the autonomous shuttles on the new Gateway North test track.
 - Secured funding from DOT to establish a regional University Teleportation Center (UTC).
- The NC-CAV Center leveraged the provided funding by NCDOT to
 - enhance outreach activities to inform the general public and increase the public awareness about emerging transportation technologies, and
 - to engage and develop collaboration with the industrial partners in terms of advanced transportation technology
- In terms of NC-CAV research on CAV impacts on traffic flow and revenue:
 - NC-CAV researchers investigated CAV Impacts on Traffic Intersection Capacity. The team conducted a comprehensive analysis of intersection-capacity with the consideration of different levels of CAV market penetration; identified potential traffic intersection scenarios over 3 intersections in North Carolina and developed the guidelines on intersection-capacity adjustments at different CAV market penetration levels.

- NC-CAV researchers also investigated the CAV revenue impact. NCDOT's revenue portfolio is heavily reliant on the taxation of motor fuels. We investigated the impact of the adoption of CAVs on the financial sustainability of North Carolina's transportation system and NCDOT's revenues.
- In terms of NC-CAV research on CAVs' required infrastructure and North Carolina readiness for adoption of CAVs:
 - NC-CAV researchers investigated the current public agency programs that may be impacted by the changes to traditional infrastructure needed to safely deploy CAVs statewide,
 - NC-CAV researchers expanded on a low-latency edge computing architecture and a software-defined vehicular edge computing (SDVEC) framework that can support CAV applications needing extensive computation or timely response, and
 - NC-CAV researchers provided recommendations to NCDOT to increase statewide readiness for CAVs in both traditional and emerging infrastructure.
- In terms of NC-CAV research on CAVs testbed and applications:
 - NC-CAV researchers developed a nationally recognized testbed of CAVs and an AV rural test track for testing advanced transportation systems and implementing emerging driving scenarios. The developed testbed of CAVs and the developed Hardware-in-the-loop (HIL) CAV simulation that can be used for creating driving scenarios which involve advanced transportation technologies including the CVAs. The open hardware and software of the developed testbed and simulator allow our research team to adjust and adapt to different driving scenarios to support pilot programs of interest to NCDOT. A state-of-the-practice AV rural test track was also developed to facilitate testing of different complex driving scenarios.
 - NC-CAV researchers developed a cooperative control approach for heterogeneous CAVs for on-demand mobility applications. We also developed a vehicle dispatch algorithm for optimally assigning passengers to vehicles and optimally routing them to their destinations. The algorithm is efficient since it assigns passengers to vehicles based on a one-to-one manner. This algorithm can be extended and incorporated into NCDOT's public transportation system to facilitate an effective means of transport.

We believe these developments provide insight into CAV impacts on transportation systems, traffic flow, and NCDOT revenue along with recommended adjustments to adapt to emerging technologies in the era of CAVs. These developments also provide insight into current public NCDOT programs and policies that may be impacted by (or required to be adapted to) the changes to traditional infrastructure to safely deploy CAVs statewide.

The developed technology under NC-CAV are enabling steps toward advanced vehicular applications in real scenarios in accordance with emerging communication and computation technologies to enhance safety and efficiency of transportation systems. According to a WHO report, traffic death is a global concern nowadays. The developed research and tools also assist NCDOT to plan for required changes in policies, programs, and infrastructure to be compatible with near-future infrastructure standards and emerging AV technologies.

APPENDICES

FOR FINAL REPORT

**North Carolina Department of Transportation
Research Project No. TCE2020-03**

**NC Transportation Center of Excellence on
Connected and Autonomous Vehicle Technology (NC-CAV)**

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APPENDIX: A
Comprehensive review of the state-of-the-practice of CAV technology

Appendix A Comprehensive review of the state-of-the-practice of CAV technology

A.1 Overview of Connected Autonomous Vehicles

CAVs are emerging transportation technology that will revolutionize the future of transport services, policy, and planning [228]. In this research, we consider three main components of CAVs, i.e., autonomous vehicles (AVs), communication infrastructure, and road infrastructure.

AVs rely on various types of sensor technologies and control theories to perceive the environment and make logical decisions, respectively. CAVs can be thought of as networks of AVs that take advantage of different modes of communication to connect with other vehicles, roadside infrastructure, cloud, pedestrians, etc. An AV is typically equipped with a powerful onboard processing unit, large-capacity storage device, and numerous sensors to obtain a clear view and understanding of its surroundings. With these sensing and computing capabilities, AVs can observe their surrounding environment, detect, identify, and track different kinds of objects, and interpret this information to generate a navigation path while respecting the transportation rules and accommodating the safety of the passengers and road users with a high level of autonomy. However, AVs are yet to be ready to deploy in real-world driving conditions [318]. In this vein, it is important to define the level of automation/autonomy in autonomous vehicles that one can rely on. The Society of Automotive Engineers International (SAE) has defined different levels of autonomy [268] for AVs: driver control (Level 0), the vehicle assists/augments primary driver control (Level 1), the vehicle having at least one automated driver assistance system (Level 2), both the vehicle and driver control safety-critical functions (Level 3), fully autonomous in certain driving scenarios (Level 4), and fully autonomous in all driving scenarios (Level 5). The National Highway Traffic Safety Administration (NHTSA) adopted the SAE's taxonomy for the automation levels and now this taxonomy has become the most commonly used as an industrial standard [226]. According to the Federal Automated Vehicles Policy of the U.S. Department of Transportation (DOT), a vehicle is denoted as AV if it qualifies the automation levels 3-5 [226]. The AVs' automation technologies at Levels 1 and 2 are commercially available today, while some of Level 3 technologies are under development and are still being tested for commercial applications. Even below automation level 3, the driving assistance system can provide drivers with some useful traffic information that is critical for safety or cannot otherwise be obtained by the driver. The information from the sensors could help the drivers in the adjustment of their driving strategies and in avoiding possible collision(s) or traffic congestion. While significant effort is being made to further mature Level 3 technologies, some efforts are pursuing a direct jump to Levels 4 and 5 to avoid the challenges such as driver dis/re-engagement when passing/taking over the control of the car [35].

The next component of CAVs includes a wide range of communication modules, e.g., Vehicle-to-Vehicle (V2V), Vehicle-to-Infrastructure (V2I), Vehicle-to-Pedestrian (V2P), Vehicle-to-Others (V2X) communications. These communication modules can be used to inform AVs about non-cooperative road users, situational awareness, and road traffic conditions. For example, the V2V communication is designed for platooning of vehicles, the V2P framework is designed to provide situational awareness and hazard detection based on the interaction with pedestrians, and the V2X communication is designed to concurrently guide CAVs at signalized intersections. CAVs' communication infrastructure is crucial to exploit application requirements such as adaptability, on-demand mobility, scalability, and interpretability [266]. Connectivity of CAVs makes it possible to notify the vehicles and drivers in advance about the traffic information (such as vehicle's speed, location, gap to the front vehicle, or if an accident occurred ahead), and possible collision(s) with pedestrians or other vehicles. Such information aims to assist drivers to reduce travel time and avoid potential crashes that often cannot be observed/predicted by the driver (with ease) on his/her own. Meanwhile, the information for speed coordination and route (re-)planning enables CAVs to improve mobility, safety, efficiency, and reduce air pollution. According to the NHTSA, CAV technologies have the potential to decrease about 80% of non-injury vehicle crashes [313]. Through V2V communication, drivers could be alerted to the potential causes of a crash such as merging vehicles, vehicle(s) in the driver's blind spot, or a sudden brake of the front vehicle. Through V2I communication, drivers could be alerted about red lights, working/school/no-passing zones, and speed limit violations.

On the other hand, CAVs' road infrastructure component is still in its infancy stage. To build a well-balanced CAV system, some of the major components of road infrastructure that are needed to be considered: traffic signs and road markings, incident and roadworks communications, digital communications, pavement structure, road surface, parking service stations, safe harbour area [191]. Public and private investments in road infrastructure are essential to creating the enabling environment for a well-functioning CAV system.

A.1.1 CAV Stakeholders: For the successful and large-scale deployment of CAVs, a joint effort of CAV stakeholders is crucial. Shown in Fig 46, major stakeholders in the CAV space can be divided into five categories: public agencies, private entities, semi-private organizations, industry partners, universities, and research institutes [254]. Two notable public agencies in the CAV space are Departments of Transportation (DOT) and Metropolitan Planning Organizations (MPOs). Private entities constitute transportation engineering and planning consulting firms. In semi-private organizations, different toll agencies and third-party government service providers are involved. Industry partners such as CAV equipment vendors, transportation technology software developers, and automobile original equipment manufacturers are covering a significant role in the CAV space. The next CAV space category includes researcher and scientists in universities and research institutes and organizations. As the application and deployment of CAV technology are interdisciplinary, it requires extensive collaboration among all the stakeholders.

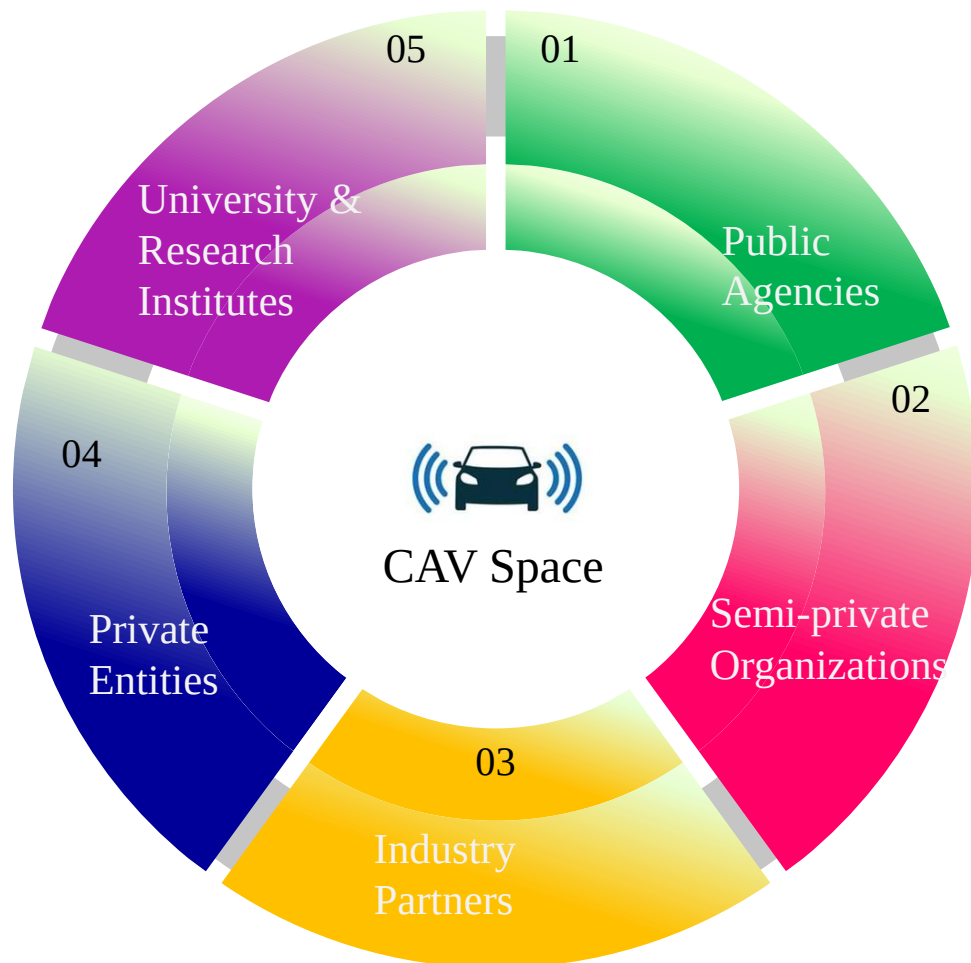


Figure 46. Major stakeholders in the CAV space.

A.1.2 CAV Use Cases: CAVs and their use cases are expected to make the transportation system more efficient, user-friendly, and safe. In this subsection, we will describe some of the potential use cases of CAVs. Some of the most common explored CAV use cases include (i) vehicle platooning, (ii) lane changing, (iii) intersection management, (iv) vehicle energy management, (v) road friction estimation, and (vi) Mobility-on-demand [214].

Vehicle platooning offers several benefits like increasing traffic flow while reducing traffic shockwaves, reducing fuel consumption, and pollutant emissions, and improving road safety. Vehicle platooning can enhance the traffic flow by reducing the inter-vehicular gap, resulting in reduction of fuel consumption and pollutant emissions. Furthermore, the interactions between vehicles and the enhanced automation in a platooning use case improve road

safety through tight control of the inter-vehicular gap and speed [214,352].

CAV deployment can also facilitate lane-changing maneuvers and significantly impact transportation traffic flow and safety, particularly on highways. Efficient lane changing can reduce traffic flow oscillations, especially in dense traffic situations. Also, vehicles that can change lanes autonomously and in connection with other cars, have the potential to reduce the risk of lane change crashes [350]. Besides, determining the optimal target lane will enhance traffic flow.

Intersection management is another aspect that can be impacted by CAV deployment, resulting in keeping traffic safe, improving traffic flow, and reducing energy consumption. The communication between autonomous vehicles and roadside units in intersections can reduce mistakes similar to human-driven vehicles and improve the efficiency of intersection management systems, thereby improving safety and energy consumption. Vehicle energy management is influenced by global optimal Speed Advisory Systems (SAS). SAS provides the optimal speed profile for connected autonomous vehicles to consume less fuel by operating vehicles efficiently [214].

Adapting to the higher level of autonomy is highly challenging due to the uncertainty in the environment, e.g., uncertain/dynamic detected objects and unpredictable pedestrians and other drivers' behaviors [35]. To achieve successful autonomous navigation in such challenging situations, combining a variety of sensing and communication technologies is critical [74]. The AVs' sensing technology is limited to its local sensing range which is highly vulnerable to extreme weather or road conditions [316]. This limitation is highlighted by the fatal accidents of Tesla car with autopilot and Uber self-driving car [338]. CAVs, as networks of AVs, leverage different modes of communication to provide greater levels of environmental awareness that transcends the limited capabilities of individual autonomous vehicles and even human perceptions [140]. The interconnectivity of CAVs enables cooperative sensing and control features that unlock a wide range of new capabilities for AVs. This includes but not limited to cooperative sensing and mapping [65], cooperative adaptive cruise control (CACC) [282], and intelligent driving assistance system (IDAS) [67].

Finally, by adopting the CAV technology, it is possible to realize Intelligent Transportation Systems (ITSs), which facilitate numerous autonomous applications [184, 259, 356]. In particular, it will be possible to implement Mobility-on-demand (MOD) services at scale, which will significantly advance the urban mobility by minimizing the overall travel and wait times of passengers. CAVs can be used in a wide range of MOD applications such as ridesharing, ride-hailing, carsharing, and even for delivery services such as food or goods. A real-world application of CAVs for carsharing services was illustrated in a joint program by Toyota and Park24 Company Limited in Tokyo [308]. CAVs can also provide equitable mobility services by providing opportunities to people who cannot afford a vehicle, people who prefer not to drive, people with disabilities, and older adults who cannot drive safely on their own. The communication and automation technologies also enable CAVs to drive more smoothly than human drivers due to reduced following gaps, harmonized speeds, and reduced stop-and-go frequencies, which in turn reduce the vehicle emissions into the environment. As another interesting application, with the help of a smart parking system, CAVs could get information about nearby parking lots and park themselves automatically after arriving at the destination. This technology could save a lot of time for travelers. Additionally, CAVs can save/rationalize land use and can improve the future infrastructure design, drive on narrower lanes, reduce the median barriers, and even reduce the number of traffic lights compare to the current road infrastructure. In summary, CAVs could bring several potential benefits including improvements in safety, efficiency, roadway/intersection capacity, mobility, and reduction in-vehicle time and vehicle emissions.

A.2 CAV Impacts: A statistical Perspective

According to the United Nations, the world population is projected to reach 9.8 billion in 2050, and 11.2 billion in 2100 [220]. This will require the adoption of new technologies for more efficient use of resources in all domains including transportation systems, to respond the growing demands for moving both goods and people. CAVs have gained attention worldwide both by industries and academia due to their numerous potential benefits and applications to the transportation system [152]. Automotive industries are focusing on manufacturing AVs that can be integrated into CAV fleets. On the other hand, researchers in academia have conducted studies on CAVs' impacts [152].

The benefit-to-cost (B/C) ratio is a commonly used evaluation metric for analyzing the impacts of CAVs. For a successful project, B/C needs to be greater than one. The qualitative estimated B/C of different sub-components of CAVs shows promising results. Some studies suggest that with the deployment of CAVs, the estimated B/C ratio for traffic intersections could range between 3.2 and 4.8 [254]. Similar studies also suggested that B/C ratio for road segments could range between 3.2 and 4.8 [254].

CAVs are also expected to significantly impact the traffic system, e.g., by increasing road capacities and

reducing the congestion. A study of the Improved Intelligent Driver Model (IDM) for AVs [143], under the assumption of Constant Acceleration Heuristics (CAH) of leading vehicle, suggests that the road capacity can be essentially improved, even with only 50% Market Penetration Rates (MPR) of IDM-CAH controlled vehicles. In addition, the communication among CAVs further allows the Cooperative Adaptive Cruise Control (CACC) would have a slight impact on the traffic flow. In [283], it is indicated that a 40% market penetration rate (MPR) of CACC equipped vehicles is a critical threshold to achieve a 10% improvement of the capacity. Also, 100% MPR of CACC equipped vehicles could double the capacity compared to the scenario with 100% MPR of Human Driven Vehicles (HDVs). There are also several studies available in the literature that provide the statistics for improvement in traffic flow and congestion under 100% MPR of CAVs using different strategies for traffic control at intersections. Compared to a traditional actuated signal control scheme, a jointly optimized signal timing and trajectories of the CAVs could increase intersection throughput by 2.7–20.2% and reduce the average delay by 16.2–36.9% based on different traffic demands, [171]. In [37], it is claimed that the introduction of an adaptive signal control could improve the average performance metric of an intersection by 10% to 50%. Lee and Park in [159] proposed a cooperative CAV-intersection control system that showed the potential of the improvement in the throughput by 8% and that in total could reduce the travel time by 33% as compared to an actuated signal control system.

Based on the rate of its adoption, the CAV technology will lead to considerable economic impacts [260]. CAVs are expected to have economic impacts of 1.2 trillion or 3,800 per American per year [53]. Intel Corporation and Strategy Analytics [264] has forecasted that the economic effects of autonomous vehicles will total 7 trillion in 2050 based on the assumption that fully automated Level 5 vehicles will be available by 2050. In a study conducted by Adler et al. [14] about the taxes associated with transportation expenditures of a selected group of the member countries of the Organization for Economic Cooperation and Development (OECD), the introduction of autonomous-connected-electric-shared vehicles (ACES) will result in a significant revenue loss to government revenue as fuel and vehicle taxation are 5–12% of federal and up to 30% of local tax revenues [14]. In [97], the direct effects of AVs on tax revenue was studied for six states: California, New Hampshire, New York, Ohio, Tennessee and Texas. The study concluded that the revenue losses due to direct effects of the AV technology depends upon the characteristics of AVs and the tax structure of the state, and suggested that states should reform transportation-based tax structures. CAVs will also create disruptive innovations such as shared Mobility-as-a-Service (MaaS), which will change the business models and replace the trends of owning personal cars and transportation companies by using autonomous driving [264].

The fuel-based transport sector has been considered as responsible for significant amounts of Green House Gas (GHG) emissions for the past thirty years or more and the road-based travel is responsible for the largest share of CO_2 emissions [152, 294]. For example, in the USA, the transportation sector was reported to have consumed around 28% of the total energy in the year 2019, and the total amount of CO_2 gas emissions by transportation was reported to be around 1864.70 million metric tons [309]. The adoption of CAVs potentially can reduce the effect of carbon emission in the transportation sector [254]. For instance, authors in [42] mentioned that automated acceleration and braking technologies associated with CAVs technologies could reduce fuel consumption by at least 20%. This is due to the fact that CAVs help improve driving decision-making and optimize the driving cycle by eliminating heterogeneity among the drivers. In [103], researchers mentioned that eco-driving associated with CAVs could reduce fuel use in the range of 15% to 20% based on the driving behaviors. Based on different scenarios, fuel economy can be improved by a 4% to 10% through eco-driving mentioned in [23]. In [30], it is mentioned that even when drivers remain “in-the-loop” of vehicle operation in the scenario of mix-modality of automation, CAVs can provide dynamic feedback to drivers that results in up to 20% fuel savings and reduced CO_2 emissions. Experimental results in [294] state that cooperative communications between vehicles can reduce CO_2 emissions up to 12%. Another study reported in [152] suggested that with the application of CAVs, GHG emissions are expected to decrease between 5% and 60%. CAVs’ applications like platooning is also expected to increase fuel savings, by reducing air resistance for cars following the leading car of the platoon. Another study described in SARTRE project stated that with the application of platooning, it is possible to reduce the fuel consumption up to 20% [152].

CAVs also could enhance the road safety. Nation Highway Traffic Safety Administration (NHTSA) reported that in 2020, there were 35,766 fatalities and 1,593,390 people were injured in road accidents [227]. In many cases, driving errors were responsible for these traffic crashes, and deployment of CAVs could reduce the number of crashes [254]. However, the exact evaluation of CAVs’ safety impacts has been a major challenge due to the lack of real-world CAV deployment data. In the absence of real-world data, simulation-based safety evaluation algorithms, such as Surrogate Safety Assessment Model (SSAM) [241] have proved to be a useful solution for analyzing the impacts of CAV deployments. In [241], authors demonstrated that with the adoption of CAVs, traffic conflicts

could be reduced by 12–47%, 50–80%, 82–92% and 90–94% for 25%, 50%, 75% and 100% CAV penetration rates, respectively. In [314], authors mentioned that based on the different autonomy levels, it is possible to avoid 28 – 73% of pedestrian crashes by using autonomous vehicles.

A.3 CAV Sectors' State of The Art

A.3.1 Current State of Autonomous Vehicle Technology: AVs rely on sensors to perceive the surrounding environments and make driving decisions. The safe and reliable operation of AVs is heavily dependent on the reliability of their sensors, actuators, computing resources, and communication modules, as well as, their perception and control algorithms. A wide variety of sensors and their measurements related to the vehicle's self-sensing, localization, and surroundings-sensing/mapping are utilized to enable the full-fledged self-driving capability. Sensors such as odometers, inertial measurement units (IMUs), gyroscopes, and information from Controller Area Networks (CANs) are used for self-sensing purposes. Typically, the information from the IMU and GPS sensors is combined to localize the vehicle on a global scale. On the other hand, sonar, RADAR, LiDAR, camera, laser scanner sensors are used to build maps and localize the vehicle on a local scale. The autonomy algorithms in an AVs fuse the sensor information to perceive their surrounding environment, find a feasible route, generate an optimal path, and track a desired path to the destination.

A.3.1.1 Autonomous Vehicle Development: Research Platforms: In the literature, there is a rich set of works on the development of sensing, fusion, and control algorithms for autonomous vehicles. In 2007, the Team Berlin introduced the “*Spirit of Berlin*” which is a drive-by-wire design for a conventional vehicle that participated in the DARPA Challenges [32]. The “*Spirit of Berlin*” had a GPS/IMU for a precise navigation, camera sensors for lane marking detection, and a long-range laser scanner for obstacle detection. “Talos” from MIT and “Junior” from Stanford University also attended the DARPA urban challenges [163, 166] with their own hardware and software architectures. In particular, after the DARPA urban challenge, improvements were made to the perception system and the recognition algorithms of “Junior.” In the improved version, “Junior” was able to generate high-resolution maps of the environment for localization of the car and use more accurate object detection algorithms. The autonomous vehicle developed by Carnegie Mellon University (CMU) in 2013, used LiDARs, radars, and camera sensors to perceive the surrounding environment [331]. This vehicle included minimal modifications to the appearance of a standard car and offered a smooth and comfortable trajectory generation and tracking. Since, the design, implementation, and testing of AVs under a wide range of simulation scenarios, and use case development in realistic traffic conditions is costly, time-consuming, complicated, and often un-reproducible, the Cognitive and Autonomous Test (CAT) Vehicle testbed incorporates hardware in the loop (HIL) that mimics the real world vehicle capabilities [33].

A.3.1.2 Autonomous Vehicle Development: The Commercialized Efforts: There is considerable and growing interest in investigating the technologies of AVs. As of today, several tech companies like Cruise, Waymo, Voyage, Nuro, Auro, Swift Navigation, Embark Trucks, CARMERA, Zoox, and Nauto are independently developing their AV prototypes. Some of the autonomy technologies developed by institutes and universities are also rapidly being transformed into the commercialization stage. To prevent traffic accidents, optimize travel time, and reduce carbon emissions, “*The Google Car*” was introduced in 2010, which is currently known as Waymo's self-driving vehicle [253]. By 2017, Google's AV fleet, “WAYMO,” has completed three million miles of test driving in the U.S. The most popular Waymo self-driving vehicle platform builds upon the Chrysler Pacifica Hybrid minivan. Apart from the vision system and Radar, these vehicles are also equipped with three different types of LiDARs for detecting objects at a higher resolution. In 2014, TESLA announced that its AV technology would be capable of self-driving about 90% of the travel time. The “*Tesla car*” enjoys advanced autonomous features, which have improved over years [316], promising to make full self-driving capabilities available in near future. Volvo announced the development of the automated vehicle technology in 2006 and tested its AV program, “*Drive Me Pilot*,” in 2017. Volvo also plans to bring its unsupervised AV to the market around 2021. With the code name “*Project Titan*”, Apple started testing AV technologies to define the next generation of transportation [113]. Besides these developments, many other vehicle companies including Audi, BMW, Mercedes-Benz, Ford, GM, Toyota, Volkswagen, and Nissan, are also developing their commercial AVs [89]. Some of the advanced AV technologies are now available to the public. Many commercial intelligent vehicles are already equipped with adaptive cruise control (ACC), collision avoidance and alerting, parking assist systems, and lane departure warning systems [86].

A.3.2 CAV Road Infrastructure: The operation of CAVs would largely benefit from the readability of the traffic control devices (TCDs). In current practices, however, most AVs operating on different testbeds worldwide are not digitally connected (like through dedicated short-range communications (DSRC) or 4G/LTE) with the TCDs,

partly because the AV sensors cannot entirely rely on V2I connection due to the latency in communication and separate development of automated and connected technologies. Hence, AV sensors primarily rely on computer-vision or LiDAR technologies to read messages from the TCDs [267]. To support the future deployment of CAVs, one of the most critical challenges is to ensure that the TCDs are appropriately installed and well maintained, such that AVs can operate safely and effectively [110]. An early study in [233] concludes that the main infrastructure challenges for automated driving systems (ADS) are: complex urban driving conditions, temporary work zones, and low visibility due to adverse weather conditions. Specifically, lane assistance systems call for high visibility and quality of lane markings, and speed control systems require visible traffic speed signs. A recent study in [29] concludes that under normal operational conditions, some vehicle-based technologies such as adaptive cruise control and blind-spot monitoring do not require particular infrastructures. Some infrastructure-based technologies, such as lane departure warning and lane-keeping, require clear lane markings and traffic signs. Other technologies, such as traffic sign recognition, automated assistance in roadwork and traffic congestion, and auto-valet parking will require the most infrastructure changes. Besides, it is found that digital signing may be challenging for in-vehicle camera systems, but this may not be a problem for CAVs since the V2I communication technologies allow for directly sending the information displayed on the digital signboards to the vehicle.

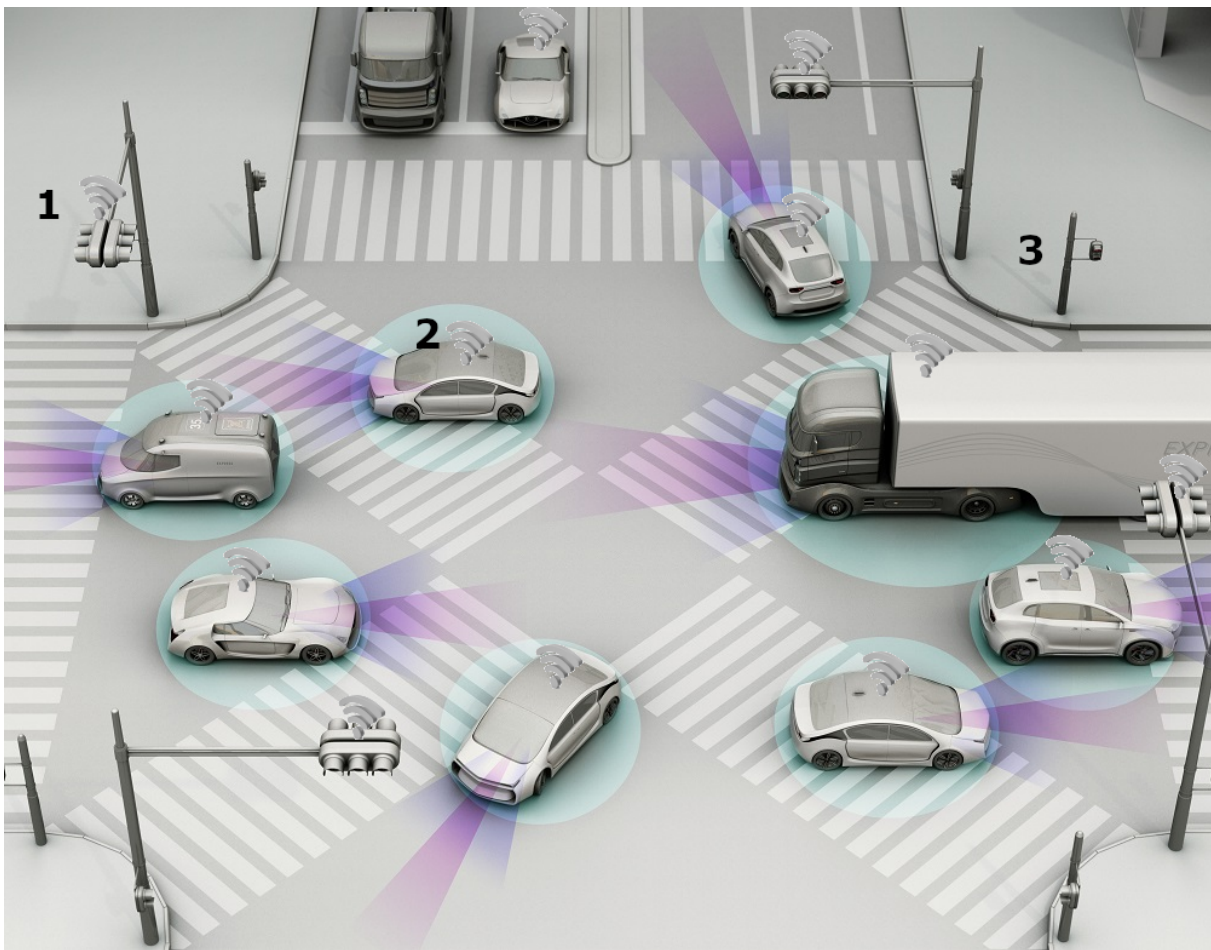


Figure 47. Proposed roadside infrastructure for CAVs: 1. Traffic Control Devices (TCDs), 2. Vehicle Communication Devices 3. Roadside Units (RSUs). CAVs can communicate with RSUs and TCDs using vehicle communication protocol. RSUs and vehicles are connected to a remote server through internet. [6].

Taking advantage of the V2I communication technology, it is expected that future traffic signal controllers can directly send signal timing information to CAVs. In V2I communication, vehicles send and receive data via the fixed roadside infrastructure components called Roadside Units (RSUs) that act as base stations and are placed on each roadway segment. RSUs communicate with the vehicle on-board units (OBU) to send and receive information

on traffic stream conditions from and to vehicles located in their immediate environment [49]. The presence of V2I not only improves safety, but also efficiency, reliability, and security. The research proposed in [210] developed a signal-head-free intersection control logic by performing a stochastic look-ahead technique based on the Monte Carlo tree search algorithm to determine the near-optimal actions (i.e., acceleration rates) for CAVs to cross intersections without any movement conflict. This approach was further expanded in [211] to follow a distributed architecture that utilized CAVs' computational resources rather than using a centralized controller. V2I communications were utilized to jointly optimize the trajectory of CAVs and timing of signalized intersections in [231, 295] and yielded significant improvements in the traffic operations. Fig. 47 represents roadside infrastructure for CAV. Another key research direction is focused on the interaction of CAVs and vulnerable road users such as pedestrians and bicyclists. This is mainly because pedestrians and bicyclists, unlike vehicles, do not need to maintain any standard regarding their visibility at night. Consequently, detecting these users might be challenging for machine vision sensors [134, 135]. Furthermore, jaywalking is common in many places. In addition, if the AV operation is forgiving, i.e., if the AVs always yield to pedestrians and bicyclists, then criminals may take advantage and pose a safety threat to the AV riders. The issue of determining the right-of-way between AVs and pedestrians/bicyclists emerged from the communication gap that exists between them. In the case of traditional vehicles, the leading cause of pedestrian crashes is the failure of the drivers to yield to pedestrians [274]. Furthermore, a large part of the communication between vehicles and pedestrians is bridged by eye contact or hand gesture, which for AVs would be a challenging task. The current human-machine-interface of AVs must learn these communication schemes [272].

In summary, the recent deployments of AVs have been made possible because their signs, signals, and markings detection algorithms have been trained with a giant archive of images of different objects. Yet, necessary steps are needed to be taken to maintain a certain standard of the TCDs so that they are visible even during low visibility conditions.

A.3.3 CAV Communications and Computation Infrastructure: New paradigm shifts and vertical technological revolutions in vehicular services have emerged toward unmanned driving, automated transportation, and CAVs. In addition to equipping with advanced environmental sensing/reasoning apparatuses (e.g., HD cameras, 3D panorama videos, point-cloud scanners, and LiDAR scanners) to facilitate autonomous driving, the next-generation driving vehicles will rely on the use of efficient mobile network infrastructures to achieve ubiquitous and prompt information exchanges [4]. For example, all-optical indicators (such as turn signals and brake lights on a vehicle and traffic lights at intersections) may be replaced by wireless signals through device-to-device communications. Vehicles may also exchange their perception data or maneuver plans with other vehicles via OBUs or acquire information from remote cloud servers or RSUs through mobile networks. Aligning with this trend, we first review the state of practice on CAV communication infrastructures in the following. We then introduce a novel computation-based vehicular edge infrastructure and its potential to enable CAV technologies through machine learning techniques.

A.3.3.1 Latest Practice on CAV Communication Infrastructure: Since the past decade, wireless networking technologies, like DSRC and the IEEE 802.11 family (802.11p) standards, have initiated wireless access in vehicular environments (WAVE) and have facilitated the information exchange between RSUs and OBUs. With a limited support for network communications via access points, transmission ranges of 802.11p can be up to 225m for vehicles with 280 km/hr relative speed. Still, it might cause packet loss at high densities with basic safety. Meanwhile, 3GPP released the service requirements to sustain the next-generation V2X applications in June 2018, which included 28 use cases to involve advanced driving, remote control, vehicle platooning and extended sensors. These V2X service requirements may involve extremely high throughput (for 3D panorama videos or point-cloud data), low latency (maneuver data for platooning), high reliability (control signals for remote driving), aperiodic transmissions (for emergency trajectory alignment), and high connection density. Since August 2018, 3GPP has launched the normative works of New Radio (NR) V2X and enhanced ultra-reliable and low latency communication (eURLLC) in 3GPP Release 16 [10], which leverages 5G cellular networks for extensive transmission ranges and advanced safety.

In the next phase of 5G standards, which is expected to be completed in the second half of 2021, the 3GPP Release 17 would extend the NR V2X operations and sidelink relay capabilities from automotive to battery-powered devices carried by pedestrians, bicyclists, or on micro-mobility vehicles, focusing on public safety. Several new features have been introduced in both academic research and industrial practice, including a new system architecture of V2X (e.g., mobile edge computing, cloud/fog networks, 3GPP local area data network, network slicing [245], etc.), new radio access schemes (e.g., millimeter-wave access, sidelink transmissions, URLLC, massive connections [175]), harmonization among various technologies (e.g., point-cloud compression, multi-view video,

3D vision, environmental perception/cognition, machine learning and artificial intelligent [47]), and new security designs. Under USDOT's requirements for real-time safety concerns [4], inter-vehicle multi-hop networking does not require infrastructure to be investigated in high dynamic operating environments. Beyond 5G networks can also supply in-time information to vehicles to assist human driving more comfortably and safely. New types of connected infrastructures can enhance the connectivity with sensing RSUs and facilitate SAE Level 3 (conditional automation) trial and deployment. However, the state of practice to support mission-critical ultra-low latency services and Level 4/5 (high/full automation) development are still in their infancy.

A.3.3.2 Intelligent Vehicular Networked Edge Infrastructure: Vehicular edge computation has emerged to allow a large amount of real-time (or low-latency) vehicular data processing close to data sources (i.e., on RSUs for network communications). It removes network bandwidth constraints to send all the data back and forth to the remote cloud server. A few studies realize such computation paradigms with edge-cloud 5G automotive systems [16] and with low-latency concerns on network modeling and radio resource allocation [261]. However, no concrete solutions exist to address the vehicular edge computing challenges. First, highly mobile and unreliable wireless links in such dynamic environments hinder network connectivity. Second, the capability of distributed processing at edges is easily overestimated, which causes unexpected failures. Third, some critical overheads require detailed investigations, such as those incurred by scaling applications into distributed edge nodes, coordinating cross-node states and storage, and handling inconsistent states delicately.

Recently, SDN is introduced to facilitate the system design and management flexibility [179], potentially solving the above challenges. SDN provides the upper-running applications with a centralized view of distributed network states, which can dramatically improve the network resource utilization, simplify network management, and promote innovation and evolution. Hence, we have proposed a new software-defined vehicular edge computing architecture called SD-VEC [183]. It enables global controllability for eURLLC requirements compatible with 5G standards and self-organizing distributed network realization for flexibility and resilience. SD-VEC offsets communication operations to computation tasks, which reduces latency while preserving reliability, and offloads primary computation to vehicular infrastructures, facilitating on-board processing [177] in CAVs. It resolves high vehicular mobility issues with machine learning enablers and proactive association and can quickly respond to CAVs via distributed near-data processing, mitigating traffic going through the network. SD-VEC involves CAVs, access points, and local edge servers and has critical components such as (i) eURLLC data plane, (ii) computing-enabled scalable control plane, (iii) latency-reliability-optimal vehicular orchestration [246], and (iv) big data-driven computing applications. By seamlessly integrating intelligence in vehicular networks, SD-VEC achieves edge infrastructure openness, programmability, and disaggregation for data-driven services. It empowers these services through data collection and processing, model training and deployment, and adaptive control with testing [38]. We are implementing and evaluating SD-VEC infrastructure in the NC Transportation Center of Excellence on Connected and Autonomous Vehicle Technology (NC-CAV) and deploying it in Greensboro to further North Carolina's and the nation's readiness for CAVs.

A.3.3.3 Data-Driven CAV Service Management & Orchestration: Realizing complete autonomous driving paradigms still requires significant technological development efforts within the next ten to 15 years, i.e., 2030-2035. Among all the enabling technologies, intelligent vehicular networked infrastructures, like SD-VEC, for the first time, can carry out a reliable, safe, real-time operation of connected transportation with the massive deployment of CAVs by exploiting data-driven optimization approaches to network control and vehicle mobility. With both historic and instantaneous data availability in the infrastructure, useful features (e.g., the correlation among vehicular events, data traffic, and service requirements) can be extracted and learned to make optimal decisions on various CAV services and their orchestration. Notably, as closely following 5G O-RAN specifications and fueled by AI-enabled mobile SDN controllers, our SD-VEC architecture implements essential CAV management tools and killer applications listed below, which catalyze future transportation developments and deployments.

- **Context-Based Anticipatory Mobility Management:**
SD-VEC supports reliable and continuous connectivity (good coverage, low delay, etc.) between CAVs and the infrastructure and allows data collection, real-time monitoring, and maintenance of CAV associations and applications. Data-driven control approaches can dynamically address handover anomalies (e.g., ping-pong, short stay) due to CAVs' high speed and the heterogeneous natural environment. SD-VEC can further use the past CAV association history to predict the following association patterns and, accordingly, take anticipatory management for vehicles' proactive access.

- **Integrated Networking, Caching, and Computing Orchestration:** leveraging SDN controllability and data-driven platforms, SD-VEC manages all resources (e.g., communications, computation, and storage) according to the quality-of-service (QoS) demands of CAV technologies and applications. Specifically, through accommodation of distributed TensorFlow learners, Spark data processors, and network slicing orchestration, SD-VEC can jointly optimize service caching, task offloading, and data migration among OBUs, RSUs at edges, and the cloud regarding specific QoS requirements. This capability considerably minimizes the end-to-end operation latency while retaining long-term energy consumption.
- **Distributed Privacy-Preserved Intelligence:** edge data analytics in SD-VEC can filter or pre-process sensitive CAV data, avoiding information leakage in backhaul and cloud servers. Also, context-based mobility management only relies on past vehicle traces than private GPS information for precise control. Therefore, SD-VEC can perform federated learning models with decentralized edge training to fulfill control operations or services of interest while preserving data privacy.
- **Safe and Connected Communities:** SD-VEC successfully brings intelligence and learning into vehicular infrastructures for data-driven CAV services. For improving public safety, it can revolutionize warning systems in school zones by harmonizing critical components, ranging from last-mile sidelink capabilities with multi-mode signal fusion, low-latency content delivery infrastructure to near-data processing and inference. SD-VEC also substantially benefits truck platooning and CAV dispatching in the States with connected transportation development.

A.4 Current State of CAV Practice

As of today, aside from efforts on components of CAVs, a vast majority of CAV deployments primarily focuses on the theoretical developments. Recently, there are some studies that aim to address the need for a realistic validation of CAV strategies to ensure maximum traffic throughput, safety under the different road, traffic, and environmental conditions including different human or autonomous driving behaviors in different experimental settings [45, 238, 277]. Only few training and testing facilities are reported in the literature. Notable examples include the VENTURER project in UK [142], the smart transportation testbed (I-STREET) on the University of Florida (UF) main campus [238], the USDOT's Connected Vehicle in Southeast Michigan [91].

The deployment of CAVs in urban settings depends on the different applications of CAVs and the readiness of cities' communication infrastructures [355]. Towards the design of CAV architectures, in [84, 119, 214], different frameworks are developed based on some essential features such as the cooperation within and across the key components in the road transport systems to enable the beneficial applications of CAVs. The works in [104, 349] develop and review different control algorithms such as platooning, lane changing, navigation, intersection management, etc. for the smooth operation of CAVs in different scenarios. The reduction of traffic conflicts, ensuring reliable travel times and the safety impacts are also analyzed in [241, 344]. Also, there are some simulation-based efforts that explore different hardware and software components in simulated environments to verify safety critical control applications such as reacting to traffic signals, tracking a target vehicle's speed, etc. [277, 357]. Different concepts of interconnected transportation networks, vehicular communication protocols, and cloud-based control of CAVs are discussed in [48, 118, 356] for improving the road safety, traffic efficiency, availability of infotainment services, enhancement of V2X services using LTE networks and possible 5G solutions. Despite these developments on CAV components, there does not yet exist a complete CAV platform that has typical components/features including a network of AVs that can provide communications with road infrastructure, road users, cloud, etc., and is tested beyond closed tracks.

A.5 Future Challenges for Development and Deployment of CAVs

As highlighted in the previous sections, while CAVs are being tested in real-world conditions, tests on CAV and TCD interactions are quite rare and mostly limited to simulation-based approaches [230], or closed tracks. The main reason is that existing traffic control devices are not completely compatible with CAVs yet. Making TCDs connected to the CAVs requires significant infrastructure improvements, which are costly and time-consuming. Besides, the state and the local departments of transportation are reluctant to make these changes, as they require major modifications to existing infrastructure, frameworks, and workforce. Therefore, one of the remaining challenges for years to come will be testing CAVs and TCD interactions in real-world conditions, which could lead to significant improvements in traffic operations and safety.

Another future challenge is the consideration of interactions between CAVs and non-motorized road users

such as bicyclists and pedestrians. Three main factors make these interactions challenging: pedestrians and bicyclists (a) may not be visible to CAVs, especially at nighttime, (b) do not require to maintain communications, and (c) have inconsistent and at times unpredictable responses. In addition, the interactions of CAVs with human-driven vehicles are still under research. Human drivers have shown significantly different responses, especially while drivers follow an AV. CAV interactions with pedestrians, bicyclists, and human-driven vehicles need to be tested under real-world conditions to ensure both safety and operations efficiency of CAVs under different prevailing conditions.

The end-user's perception of the CAVs is another future challenge. This perhaps is the most important challenge that needs to be addressed to allow the wide adoption of CAVs. Users seem to be skeptical about the safety and reliability of CAVs. The recent Tesla crashes have contributed to more skepticism. Testing CAVs in facilities that are perceived as safe can help to reduce skepticism. For instance, testing a CAV in a signalized intersection is perceived as more dangerous than making the test in a roundabout, where crossing conflicts do not exist. The lack of uniform ruling across the world on allowing CAVs on roadways not only hampers CAV adoption but also contributes to negative user perception of CAVs.

Reliability in communications among CAVs, other road users, and TCDs is very crucial. Existing tests, especially in the transportation engineering domain assume perfect communication and do not deal with real-world implications that may arise. On the other hand, tests in the communication engineering domain only focus on CAV communications with other CAVs. Besides, the cyber-security of CAVs needs to be ensured to prevent malicious acts.

A.6 Conclusions

This research provided a review of the state of the practice of CAV technologies, including the efforts in the development of autonomy technologies, communication backbone, and computation needs. Furthermore, this research identified some inevitable impacts of CAVs on roadway design, traffic control device standardization, and the infrastructure needs to facilitate real-world CAV deployments. This research also identified some major challenges that need to be addressed in the near future. There is a need to study CAVs and TCD interactions in real-world tests and under realistic conditions. The interactions of CAVs with other road users such as pedestrians, bicyclists, and human-driven vehicles are not known and need real-world tests. The effects of communication loss or delay on the safety of CAVs and traffic operations in transportation facilities need to be researched further. Finally, one major challenge to overcome for the wide adoption of CAVs is end-user perception. Users need to feel safe and comfortable with CAVs, otherwise, they remain skeptical of this new technology. Uniform standards and rulings on CAVs across the world can improve user perception and facilitate worldwide CAVs adoption.

APPENDIX: B
**Impact of Connected and Autonomous Vehicles (CAVs) on North Carolina's Transportation System and
Associated Revenue**

Appendix B Thrust 1: Impact of Connected and Autonomous Vehicles (CAVs) on North Carolina's Transportation System and Associated Revenue

B.1 LITERATURE REVIEW

B.1.1 Introduction

This report provides a comprehensive review of the current state-of-the-art and state-of-the-practice on connected and autonomous vehicle technology and its impacts on traffic intersection capacity. This should give a clear picture of CAV technology, deployment and market penetration rate prediction of CAVs, traffic flow controls of CAVs, control strategies for CAVs at intersections, intersection capacity analysis methods, and intersection modeling scenarios and parameters used in the existing evaluation studies on the impacts of CAVs at intersections.

The rest of this chapter is organized as follows. Section B.1.2 presents concepts and taxonomy of connected vehicle (CV), autonomous vehicle (AV), and CAV technologies, followed by the descriptions of current technologies in use and benefits of CAVs. Section B.1.3 shows existing deployments and market penetration rate prediction of CAVs. Section B.1.4 introduces traffic flow control strategies for automated vehicles and CAVs. Section B.1.5 presents control strategies for CAVs at intersections. Section B.1.6 discusses several studies using empirical and simulation methods to analyze the capacity impact of CVs/AVs/CAVs at intersections. A variety of suitable evaluation criteria for measuring intersection system performance and assessing possible impacts of the mixed flow of Human-Driven Vehicles (HDVs) with CAVs are evaluated and presented. Section B.1.7 summarizes several intersection modeling scenarios developed and specific parameters used when modeling CAVs. Finally, section B.1.8 concludes this chapter with a summary.

B.1.2 Connected and Autonomous Vehicles Concepts and Potential Benefits

The term 'intelligent vehicles' refers to vehicles that are equipped with communication and/or autonomous driving technologies. This part of report gives the concepts, taxonomy, and potential benefits of the CV, AV, and CAV.

B.1.2.1 Connected Vehicles (CVs)

Concepts of the Connected Vehicles

Connected vehicles (CVs) are vehicles that are implemented with wireless communication technologies to facilitate vehicle-to-vehicle (V2V), vehicle-to-infrastructure (V2I), and vehicle-to-pedestrian (V2P) communication. Specifically, CV denotes the manual or autonomous vehicle which is capable of communicating with other vehicles/infrastructures/people to collect or transmit information on the driving environment to guide driver's maneuvers [125]. The V2V communication can transfer the state of the subject CV (e.g., speed, acceleration, and location) to surrounding CVs to implement applications such as hazard alerts, lane changing assistance, and rear-end/head-on collision avoidance. V2I communication can enable vehicles to obtain information from the infrastructure including signal stage, speed, volume, travel time, queue length, and stops. V2P communication allows vehicles to communicate with pedestrians' smartphones and provides warnings to avoid vehicle-to-pedestrian collisions especially for pedestrians in blind spots.

Potential Benefits of the Connected Vehicles

According to the National Highway Traffic Safety Administration (NHTSA), CV technologies have the potential to decrease about 80% of non-injury vehicle crashes [313]. By applying connected vehicle technologies, drivers can be notified in advance of the traffic information (such as vehicle's speed, location, gap to the front vehicle, an accident that occurred ahead), and possible collision with pedestrians or other vehicles. Such information aims to assist drivers to reduce travel time and avoid potential crashes that cannot be observed/predicted by the driver. Meanwhile, information for speed coordination and route re-planning enables CVs to improve mobility, safety, efficiency, and reduce air pollution.

As improving safety issues are the main objective of CVs, Table 17 summarizes the potential safety benefits and the maturity of CV technologies. Through V2V communication, drivers could be alerted to potential causes of crashes such as merging vehicles, vehicles in the driver's blind spot, and sudden brake of the front vehicle. Through V2I communication, drivers could be alerted of red lights, working/school/no-passing zones, and speed limit violations.

B.1.2.2 Autonomous Vehicles (AVs)

Taxonomy of Autonomous Vehicles

The basic concept of the autonomous vehicle (AV) refers to using intelligent technology to replace some or all of the human operations of driving electronic or mechanical vehicles [280]. Regarding the concept of automation,

Table 17. Safety benefits and maturity of connected vehicle technologies

Type	Technology	Safety Benefits	Safety Improvement	Maturity
V2I	Red light warning	Warning for red light	High	High
V2I	Stop gap assist	Warning for minimum stop gap	Medium	High
V2I	Reduce speed warning	Warning for speeding	Medium	High
V2I	Traffic Signal Coordination	More benefit for intersection capacity	Low	Medium
V2V	Lane Change Warning	Lane change information from CVs	High	High
V2V	Forward Collision Warning	Avoid Rear-End crashing	High	High
V2V	Electronic Emergency Brake Light	Avoid Rear-End crashing	High	High
V2V	Left Turn Assist	Opposite direction	High	Medium
V2V/V2I	Do Not Pass Warning	Opposite direction	High	High
V2V/V2I	Intersection Movement Assist	Junction crossing	High	Medium
V2V/V2I	Blind Spot Warning	Avoid traffic collision due to the blind spot	High	Medium
V2V/V2I	Emergency Vehicle Priority	Give priority to the emergency vehicle	High	High
V2X	Pedestrian Crossing Warning	Notification of pedestrian crossing the street	High	Low

different taxonomies for the autonomous vehicle were proposed. In 2013, the NHTSA proposed a 4-level category for the automation degree/level of the vehicle. Then, a 5-level automation degree category was introduced by the Society of Automotive Engineers International (SAE) in 2014. In 2016, NHTSA adopted SAE's taxonomy for the automation levels of the autonomous vehicle, and now the 2016 SAE's taxonomy for the automation level of the autonomous vehicle has become commonly used as an industry [226, 268].

Regarding the 2016 SAE's autonomous vehicle taxonomy, the increase in the automation level would correspondingly decrease the engagement of human labor required to monitor the driving environment and control the vehicle. From Level 0 to Level 5, the allocation of vehicle control function between the vehicle and the driver increases along the gradient from full driver control (Level 0), the vehicle assists/augments primary driver control (Level 1), the vehicle has at least one automated driver assistance system (Level 2), both the vehicle and driver control safety-critical functions (Level 3), fully-autonomous in certain driving scenarios (Level 4), and fully-autonomous in all driving scenarios (Level 5). Table 18 provides an outline of the five automation levels (including Level 0 which indicates no automation) [150, 226]. According to the Federal Automated Vehicles Policy of the U.S. Department of Transportation, a vehicle is denoted as AV if it has levels 3-5 autonomous systems [226]. Also, according to [280], "autonomous" is not strictly limited to a specific level of autonomy and any level of autonomy could be defined as an autonomous vehicle and this report adopted this definition for the AV.

Potential Benefits of Autonomous Vehicles

Driving includes several functions, including control, perception, planning, localization, and management. Even with an automation level less than L3, the driving assistance system notices drivers with some traffic information that is critical for safety or some information that could not be obtained by the driver. The information from the sensor could help the driver to adjust their driving strategies and avoid possible collisions or congestion.

Table 19 summarizes a total of 20 intelligent automation technologies for different automation levels and the corresponding safety benefits, safety improvement, and maturity of these technologies [150]. Presently, the technologies at Levels 1 and 2 are commercially available today, while some of Level 3 technologies are still being tested for commercial applications and are under development.

B.1.2.3 Connected and Autonomous Vehicles (CAVs)

Concepts of the Connected and Autonomous Vehicle

If any AV has V2V, V2I, or V2X functions to collect and transmit information, it is defined as a CAV [281]. CV communication technologies permit widely, timely, standardized, and secure communication with unities equipped with communications equipment. The additional information collected could help CAVs to utilize the Cooperative Adaptive Cruise Control (CACC) system. For CAVs with the CACC system, they could follow their predecessors with higher accuracy, shorter response time, and shorter headway compared to AVs with Adaptive Cruise Control (ACC) systems [284]. Therefore, CAV could be treated as the combination of the CV technologies and AV technologies, and CV technologies could supply, enhance, or have synergistic effects on AV technologies to some extent [281], though connectivity is not a mandatory characteristic of AVs [125]).

Potential Benefits of Connected and Autonomous Vehicles

As the CAVs are vehicles that are incorporated with both automation systems and communication systems, the potential benefits of CAVs combine the benefits of AVs and CVs. In summary, CAVs could bring several potential benefits including improvement of safety, efficiency, roadway/intersection capacity, mobility, and reduction in-vehicle

Table 18. Outline of five automation levels (NHTSA, 2016) [226]

Level	Vehicle Controls	Environment Monitoring
L0	No automation. Drivers are solely responsible and control all vehicle functions (braking, steering, throttle, and motive power).	Drivers take sole responsibility for monitoring the roadway environment and traffic; some systems may provide information or warnings to the driver (such as traffic sign/signal information and collision warnings).
L1	Driver assistance. Drivers are solely responsible, but drivers are assisted with primary vehicle controls (either steering or acceleration /deceleration). And only one of the primary control systems may provide assistance at any one time.	Drivers take solely responsible for monitoring the environment. And the system provides information and warnings as with L0.
L2	Partial automation. Drivers share the authority of primary controls with the system and may be physically disengaged from operating the vehicles. The system may undertake steering and acceleration/deceleration functions. Drivers can cede active primary control in certain situations and are expected to take control on short notice.	Drivers are responsible for monitoring the environment and are expected to be available for control at all times. The system could obtain driving information from the environment. Information and Warnings may still be provided to the driver.
L3	Conditional automation. Drivers can cede the system control of safety-critical functions and are expected to take control under certain conditions with sufficient transition time.	The system could obtain driving information from the environment. When ceding control and transiting back to driver control, drivers can rely heavily on the system to monitor environments.
L4	High automation. The system undertakes all safety-critical driving functions and monitors the driving environment in certain locations or scenarios. Drivers only need to provide destination or navigation input but are not expected to take control at any time during the trip.	The system will perform all the monitoring in certain driving scenarios.
L5	Full automation. The system undertakes all safety-critical driving functions and monitors the environment in all scenarios. Vehicles are not restricted by the locations and conditions they can travel to. Drivers only need to provide destination or navigation input but are not expected to take control at any time during the trip.	System could take the whole responsibility for the monitoring in all driving scenarios.

Table 19. Benefits and maturity of autonomous vehicle technologies

Automation Level	Technology	Safety Benefits	Safety Improvement	Maturity
Level 0	Adaptive headlights	Improve light condition and visibility of environment	Intermediate	High
	Forward collision warning	Prevent rear-end collision	High	High
	Blind spot monitoring	Reduce crash risk caused by blind spots (such as merging and weaving areas)	High	High
	Traffic sign recognition	Inform and alert the driver	Intermediate	Medium
	Lane departure warning	Prevent lane departure crashes	High	Medium
	Left-turn assist	Prevent potential conflict	High	Medium
	Pedestrian collision warning	Prevent pedestrian collision	High	Medium
	Rear cross traffic alert	Prevent backing collision	High	Medium
Level 1	Electronic stability control	Prevent rollover	High	High
	Adaptive cruise control	Prevent rear-end collision	High	High
	Cooperative adaptive cruise control	Prevent rear-end collision	Low	Medium
	Parental control	Prevent speeding	Intermediate	Medium
	Automatic emergency braking	Prevent rear-end collision	High	Medium
	Lane keeping	Prevent lane departure crashes	High	Medium
Level 2	Traffic jam ass	Driving assist	Low	Medium
	High speed automation	Driving assist	High	Medium
	Automated assistance in roadwork and congestion	Driving assist	High	Medium
Level 3	On-highway platooning	Driving assist, prevent rear-end crashes	Intermediate	Medium
	Automated operation for military applications	Prevent human fatalities	Unknown	Low
Level 4/5	Self-driving vehicle	Replace human drivers	High	Low
	Emergency stopping assistant	Response when lose control human drivers	High	Low

time and emissions.

As mentioned by Li and Kockelman [170], CAVs may significantly reduce the number of crashes and save current crash costs in the U.S. by at least \$ 126 billion per year. CAVs can also increase mobility by providing opportunities to people who cannot afford a vehicle, people who prefer not to drive, people with disabilities, and elder people who cannot drive safely [82]. The communication and automation technologies also enable CAVs to drive more smoothly than human drivers, with smaller following gaps and harmonized speeds, and these will also reduce vehicle emissions by reducing stop-and-go frequency. Also, with the help of the smart parking system, CAVs could get information on nearby parking lots and park themselves automatically after arriving at the destination. This technology could save lots of time for the passengers. Additionally, CAVs could save/rationalize land use and improve the infrastructure design by narrowing the width of the lanes and removing median barriers and even traffic lights in the future.

B.1.3 Deployment of and Market Forecast for AVs: With the rapid development of vehicle automation and communication technologies, Level 1 and Level 2 automation systems have already been commercially implemented in intelligent vehicles for many years. Meanwhile, Level 3 conditional automation systems are still under development and are being tested in different experimental fields. Moreover, Level 4 AVs (conditional automation vehicles) can reduce driver stress and increase productivity, and Level 5 AVs (fully autonomous vehicles) are expected to significantly improve system performance.

B.1.3.1 Deployment of the Autonomous Vehicles

The vision of vehicle automation was initiated as early as 1918 [244]. In 1939, General Motors exhibited the concept of AV, and the autonomous technology was mainly concentrated on controlling speed, break, lane change control, and other basic cruise control functions [284]. Even though there have lots of uncertainties as to the available time for the fully autonomous vehicle for the public, the Digital and 4th Industrial Revolutions gave a tremendous boost to rapid technological development in this field. All these intelligent technologies further promote several on-roads and experiment field tests for AVs with different autonomous technologies [52].

As early as the 1950s, General Motors and Radio Corporation of America Sarnoff Laboratory jointly initialized the early phase of research and development (R&D) of AV technologies [281]. From 1964 to 2003,

Table 20. Autonomous technology project proposed by Volvo

Start year	Autonomous technology project
2006	Collision warning with brake support
	Adaptive cruise control
	Lane departure warning
2007	Collision warning with auto brake
2008	City safety
2009	Safe Road Trains for The Environment (SARTRE) project begins
2010	Adaptive cruise control with queue assist
	Collision warning with full auto brake
	Pedestrian detection with full auto brake
2012	Traffic sign information
	Park assist pilot
	Cross-traffic alert
	Lane-keeping aid
	BLIS project (lane change assist)
	Cyclist detection with full auto brake
	Active high-beam control
	SARTRE project completed
2013	Concept of autonomous parking
	Drive Me project announced
2014	Pilot Assist
	Auto brake at intersection
2017	Drive Me pilot tested on real roads

several other AV programs were deployed and tested in different countries/areas, including the United States of America, European Union, Canada, United Kingdom, China, Japan, Australia, United Arab Emirates, Singapore, Korea, etc. [36]. Under the cooperation of government institutes, universities, and companies, several CAV-related research projects were established, including the pilot of the autonomous commercial taxi/bus, vehicle platooning, technologies of driving environment recognition, smart parking, and V2X communication [281]. In 2004, the US government accelerated the research and development of AV technology by the Defense Advanced Research Projects Agency's (DARPA) Grand Challenges Program. This program challenged AVs to traverse a desert area in 2005 and 2007. Researchers also managed to test the performance of AVs on open urban roadways through the DARPA's Urban Challenge Program [244, 281]. Since then, research and development continue to rapidly evolve in both academic and industrial fields. Other projects are also under field trials considering mixed traffic flow of AVs and HDVs, including Safe Road Trains for the Environment (SARTRE) and Europe's KONVOI system.

The automation technologies developed by institutes and universities are also rapidly transformed into commercial fields. Several commercial companies planned or started to investigate the technologies of AVs. As shown in Table 20, Volvo announced the development of autonomous vehicle technology in 2006 and tested its AV program, "Drive Me Pilot", in 2017. Volvo also plans to bring its unsupervised AV to the market around 2021. Tech giant Google also started to develop AVs in 2009. By 2017, Google's AV fleet, "WAYMO", has completed three million miles of test driving in the U.S. In 2014, TESLA announced that its AV technology would be capable of self-driving about 90% of the travel time. At present, TESLA vehicles are equipped with a self-driving assistance system. By 2020, many other vehicle companies, including Audi, BMW, Mercedes-Benz, Ford, GM, Toyota, Volkswagen, and Nissan, are developing their commercial AVs [88]. Meanwhile, Level 2 AVs and some CV technologies are now available to the public. Many commercial intelligent vehicles have already been equipped with the ACC, collision avoidance and alert, parking assist systems, and lane departure warning systems [87].

As summarized in Bloomberg [36], 36 cities around the world announced to host field tests for AVs, or planned to start piloting experiments in the near future. Meanwhile, 18 other cities are making long-range surveys of the planning, regulatory, law, and governance issues associated with the application of AVs. These piloting cities were undertaking a variety of AV application tests. The testbed locations are generally isolated places or low population-density areas of the city, such as isolated test sites, racing tracks, parks, campuses, renewal districts, highways, and former international mega-event sites. Hence, as mentioned in Bloomberg [36], even though several

trials are being undertaken, there still needs more tests to guide fully self-driving AVs in complex environments of urban areas.

B.1.3.2 Connected and Autonomous Vehicles (CAVs)

With the help of intelligent technologies from virtual identity and machine learning algorithms, some Level 3 conditional automation technologies (such as platooning and traffic congestion assistance) have been implemented in field experiments and are under test for market implementation in the near future. Figure 48 indicates that Level 2 vehicles will comprise the largest portion of new sales during the next decade (2020 – 2030). Sales for Conditional automation Level 3 and High automation Level 4 vehicles are all expected to increase steadily in the next decade. And Level 4 vehicles with highly automated systems are expected to be available for the market around 2025 [256].

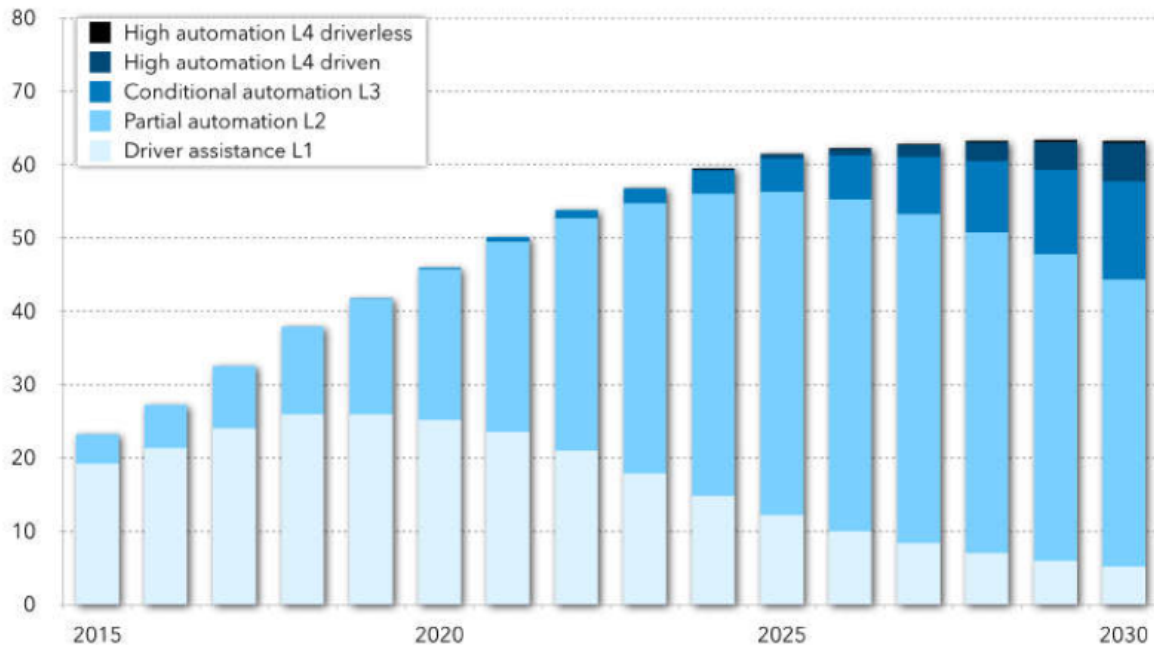


Figure 48. Prediction of sales for new passenger cars (in millions) (PTOLEMUS, 2017) [256]

However, since Level 3 AVs are still under testing for fully commercial application and the technology of full automation Level 5 is still under development phase, researchers expect that the mixed flow of Human Driving Vehicles (HDVs) and AVs would exist for a long period. Several previous studies also gave a prediction of the market penetration rate for autonomous vehicles in the next decades. Navigant Research [221] estimated that 75% of all light-duty vehicles around the world (almost 100 million sales annually) will be equipped with automation assistance systems by 2035. In accordance with this timeline, Litman [185] provided a prediction that AVs' beneficial impacts on safety and congestion are likely to appear between 2050 and 2080. Litman [185] also expected that human driving may be restricted after 2060 as the randomness of human driving behaviors might result in disruptive effects on the automation systems. Moreover, as autonomous vehicles are relatively costly and rare in the early stage, benefits, such as reducing driver stress/operations and independent mobility, are more likely to be available for affluent users in the early stage. Hence, AVs sharing might be more applicable in the early stage when AVs are available for commercial adoption. Likewise, only when the price of AVs becomes affordable for common users, benefits of the affordable taxi, micro-transit services, and independent mobility could be available for moderate-income users.

As shown in Figure 49, Litman [185] gave predictions of the sales, travel, and fleet projections of the AVs from 2030 to 2080. By 2050, with optimistic predictions, AVs are supposed to comprise 50% of all vehicle sales, 40% of all vehicle travel, and 30% of all vehicles. Meanwhile, the market penetration rates (MPRs) of the AVs are expected to be around 50% in 2060. TransAID [208] predicted the fleet penetration rates of different vehicle types (i.e., HDV, CV, AV, and CAV) from 2025 to 2060. In this report, the Level 4 technology is supposed to be feasible in 2035. And HDVs still will have 15% MPRs in 2060.

B.1.4 Traffic Flow Controls of CAVs

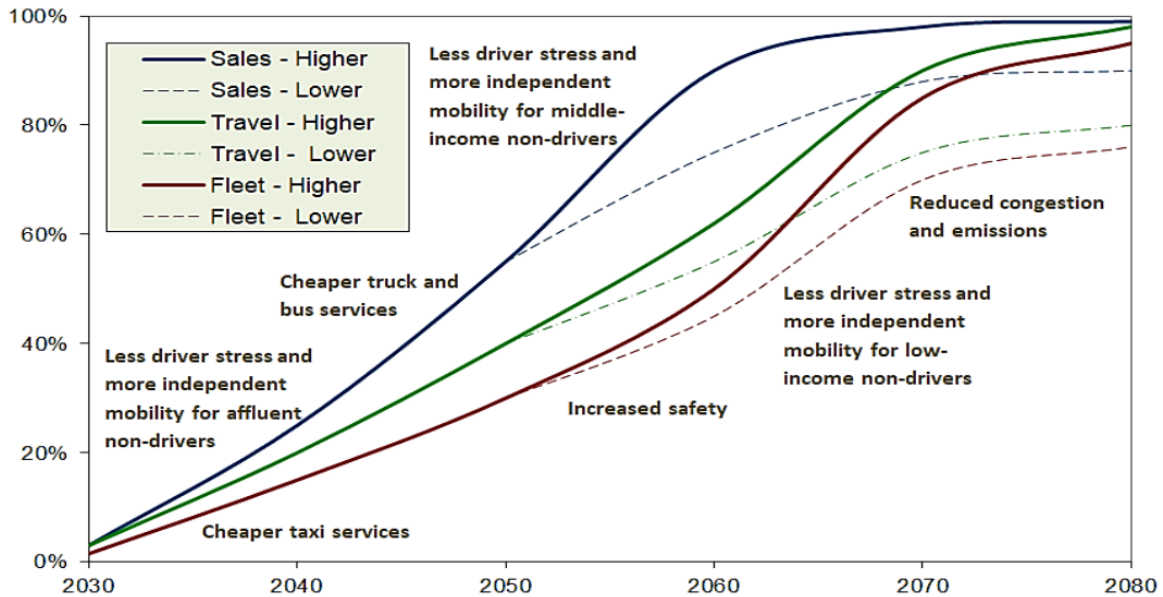


Figure 49. Prediction of sales, travel, and fleet proportion rates of AVs (Litman, 2020) [185]

CAVs are automatically or partially controlled by the designed systems. These automation systems with fixed rule/logic make the movement behaviors of the CAVs different from manually controlled vehicles. The heterogeneous driving behaviors among different drivers would result in significant randomness in longitudinal movements (travel speed and acceleration/deceleration) of the vehicles. Also, the CAV-controlled system would give a more rapid response to emergency circumstances (such as sudden braking of the front vehicle and dashing out of a pedestrian) than human drivers. The differences between CAVs and HDVs require specific models to describe the traveling behaviors of such intelligent vehicles. In the simulation, the traveling behaviors of the CAVs could be divided into two parts, i.e., a car-following control model for longitudinal movements and a lane-changing control model for lateral movements.

B.1.4.1 Longitudinal Movement Control of CAVs

The main difference between HDVs and CAVs is the controller for the longitudinal movements (which mainly controls the travel speed), acceleration/deceleration, and car following gaps between vehicles. Also, the longitudinal movements of AVs significantly improve the efficiency of the roadway/intersection systems. Hence, this part of the report mainly focuses on studies on the longitudinal movements of the CAVs.

The Lidar sensor technology allows AVs to obtain the surrounding environment information, especially on the distance and speed of the front and current vehicles. In this case, AVs could adjust their speeds according to the downstream traffic situations. Furthermore, with the communication technology (V2V, V2I, or V2X), the CAVs could communicate with each other to share their locations, speeds, and accelerations. Meanwhile, CAVs would change their travel behaviors according to the information, such as a crash ahead and intersection signals. The communication technology helps CAVs to connect and potentially form a platoon, and this cooperative traveling behavior could significantly improve the efficiency of the transportation system. All these traveling behaviors of CAVs are beyond the capability of human drivers and make the car-following behaviors of intelligent vehicles (AVs and CAVs) different from the traditional car-following behaviors and models of normal HDVs.

The Intelligent Driver Model (IDM) and MICROscopic Model for Simulation of Intelligent Cruise Control (MIXIC) models are the two most often used benchmark car-following control models for AVs, and they have been implemented in many studies, which are shown in Table 21. Several studies also modified these models to describe the longitudinal movements of intelligent vehicles. Meanwhile, the Adaptive Cruise Control (ACC) System is widely implemented in AVs. Thus, an ACC control model has been proposed and adopted in the simulation of AVs in several studies. Moreover, the Cooperative Adaptive Cruise Control (CACC) System has been widely utilized for CAVs. Hence, a specific CACC control model is proposed to describe the longitudinal movements of CAVs. The following part gives a more specific introduction to these four longitudinal movement control models for AVs and CAVS.

Cruise Control Modes

Intelligent Driver Model: IDM was first proposed by Treiber et al. [306], and it was commonly used in the simulations to control the acceleration and deceleration of HDVs and AVs based on the condition of the front vehicle

Table 21. Longitudinal movement control model for AVs and CAVs

Methodology	Vehicles	Reference paper
Intelligent Driver Model (IDM)	AV, HDV, CV	Kesting et al., 2007, 2008; Milanés and Shladover, 2014; Talebpour and Mahmassani, 2016; Treiber et al., 2000
IDM with constant-acceleration heuristic	AV, HDV	Kesting et al., 2010
Cooperative IDM	AV, CV, HDV	Zhou et al., 2017
MICROscopic Model for Simulation of Intelligent Cruise Control (MIXIC)	CV, CAV	Deng, 2016; Talebpour and Mahmassani, 2016; van Arem et al., 1997; Van Arem et al., 2006
Adaptive Cruise Control (ACC)	AV	Milanés and Shladover, 2014; Porfyri et al., 2018; Treiber et al., 2000
Cooperative Adaptive Cruise Control (CACC)	CAV	Shladover et al., 2012

in a single-lane situation [305]. The IDM has a simple model structure and accident-free logic that can be used to describe the longitudinal movement characteristics of the AV with the ACC system. Also, the IDM does not include an explicit reaction time of the driver and it has a continuously differentiable acceleration/deceleration function [305]. By modifying specific parameters according to specific cases, the IDM can be used for an AV with the ACC system or in a HDV situation.

Improved Intelligent Driver Model: In most situations, the IDM can provide plausible acceleration and deceleration rates. However, when the distance gap to the front vehicle is significantly lower than the desired distance gap, the IDM would result in an unrealistically high deceleration rate for the current vehicle to stop [77]. For HDVs, drivers would not suddenly brake/decelerate when the front vehicle is not suddenly decelerating to stop even if the distance gap is very small.

To mitigate this issue, Kesting et al. [143] further combined the IDM with the Constant Acceleration Heuristics (CAH) to determine different acceleration/deceleration rates in different scenarios. The basic assumption of the CAH was that the front vehicle will not accelerate/decelerate suddenly in the following few seconds [143]. If the IDM produces an unrealistically high deceleration and the CAH deceleration is in a comfortable deceleration range, the AV with the ACC system would decelerate at a rate of the CAH deceleration minus the comfortable deceleration. In this way, the IDM-controlled vehicle could avoid the unrealistic deceleration situation. Results showed that the road capacity is essentially improved, even with only a 50% MPR of IDM-CAH controlled vehicles.

Additionally, several other modified IDMs were applied to simulate CAVs in different situations. To improve safety in non-stationary traffic situations, Derbel et al. [73] modified the desired minimum gap between vehicles in the IDM. Zhou et al. [354] developed a cooperative intelligent demand model (CIDM) using the IDM as the benchmark model and examined the system performance of CAVs. The results showed that the increasing percentage of CAVs will reduce the total travel time and smooth traffic oscillations caused by the freeway merging or lane drop sections.

Cruise Control Systems

Microscopic Model for Simulation of Intelligent Cruise Control: The communication function helps the CAV with the CACC system to obtain information on the surrounding vehicles and infrastructures. A car-following model specific to the CAV with the CACC system is needed. A stochastic simulation model, MICROscopic Model for Simulation of Intelligent Cruise Control (MIXIC), was developed by van Arem et al. [25]), and it has been widely used for cooperative CAV simulations. The MIXIC model is capable of characterizing the V2V communication process and can share speed, acceleration, and deceleration between the front and current CAVs. Moreover, different from the IDM which only models a single lane, the MIXIC is capable to model two-, three-, and four-lane situations. This makes the adjusted traffic flow model controlled by the MIXIC more reliable and closer to the reality of CAVs with the CACC system.

The basic acceleration controller in the MIXIC model can be divided into two main parts: one is the acceleration controller part, which calculates the reference acceleration values, and another part is a vehicle model which transforms the reference acceleration values into actually realized acceleration values [315]. Therefore, the

reference acceleration rate was determined by a controller and then transformed into a vehicle model for real actions. Van Arem et al. [315] utilized the MIXIC to study the impact of CAVs with the CACC system in the highway-merging scenario from four to three lanes (lane drop scenario). The results showed that a low CACC system penetration rate (ρ 40%) would decrease the average speed, increase speed variances, and result in more shock waves before and after the merging area. Only when the CACC system penetration rate is over 60%, the CACC-equipped CAVs would improve the stability and efficiency of the traffic flow in the merging area. Talebpour and Mahmassani [297] employed the IDM and MIXIC to investigate the effects of CVs and CAVs on traffic flow stability and throughput. The results indicated that the increase in the market penetration rate of CAVs can improve the traffic flow stability and the throughput of roadways. 2.4.1.2.2 Adaptive Cruise Control System With the development of the intelligent driving assistance system (IDAS), the intelligent vehicle could control or assist with several driving tasks for drivers. An early stage of the IDAS is a cruise control (CC) system. The primary function of the CC-equipped vehicle is to maintain the desired speed set by a driver. After that, the CC system evolved toward ACC and CACC systems. These systems mainly control the acceleration/deceleration of AVs for longitudinal movements. The ACC system controls brake and throttle systems to change the travel speed and maintains a safe following gap based on a predefined speed and gap distance between preceding and current vehicles.

Numerous cruise control systems have been proposed for intelligent vehicles in previous studies. The IDM, ACC, and CACC are the three most commonly used cruise control models that control the longitudinal movements of intelligent vehicles [206, 255, 306]. The ACC system was proposed and dynamically controlled by four modes: cruising control, gap control, gap-closing control, and collision avoidance mode [206, 208, 337].

Ioannou and Stefanovic [132] found that the smoothly controlled speed of AVs with the ACC system would be beneficial to the environment. However, several studies also pointed out that the use of the ACC system was unlikely to change lane capacity significantly or even decrease the performance of the transportation systems because of the unstable interaction between HDVs and AVs [320, 339]. The disturbances among the traffic of AVs with the ACC system and HDVs are mainly caused by the high-acceleration maneuver, lane cutting-in, lane exiting, and sudden braking. Also, when a vehicle with the ACC system is following a HDV, it still needs a transfer time for the driver to take control of the vehicle for emergency circumstances. Hence, the safety distance gap between HDV and ACC vehicles is equal to or even larger than the gap between two HDVs.

Cooperative Adaptive Cruise Control System: The CACC system is a functional extension of the ACC system, and it enables cooperative platoon driving by sharing the acceleration, deceleration, and vehicle positions by V2V, V2I, or V2X communications. The additional information collected could help CAVs with a CACC system follow the front vehicle with higher accuracy, shorter response time, and shorter distance gap compared to ACC vehicles [284]. The communication allows the CACC system-equipped CAVs to have a significantly shorter time headway (i.e., 0.5 seconds) compared to the ACC (i.e., 1.4 seconds). The acceleration/deceleration of the subject CACC vehicle is controlled based on the gap distance and speed difference with respect to the preceding vehicle. In the simulation, the parameters that determine the longitudinal movements of CAVs with the CACC system are shared among the CACC platooned vehicles. Also, CACC platooned CAVs do not need to guarantee the minimum safety distance theoretically, but there still has a minimum safety distance and a collision-free function for CACC platooned CAVs to protect cybersecurity and communication delays scenarios in the simulation.

Several studies investigated the impacts of the ACC/CACC system by using the microscopic traffic simulator. Arnaout and Arnaout [26] found that the ACC-equipped vehicles would only have a slight impact on capacity. Delis et al. [72] indicated that the CACC system performs better than the ACC system with respect to both traffic stability and capacity. Amoozadeh et al. [22] tested the impact of message falsification disturbances and radio jamming attacks on the acceleration and following distance of CACC vehicles. Results indicated that security attacks could reduce traffic safety and result in traffic flow instability and rear-end collisions.

Several studies also pointed out that a significant improvement in the system performance requires a certain market penetration rate (MPR) of the CACC-equipped vehicles. Arnaout and Arnaout [26] utilized simulations to investigate the effects of the CACC on the traffic flow on a multilane highway. Results showed that low MPR of CACC vehicles would have a slight impact on the traffic flow. Shladover et al. [284] indicated that a 40% market penetration rate (MPR) of CACC-equipped vehicles is a critical threshold to achieve a 10% improvement of the capacity. Also, 100% MPR of CACC-equipped vehicles could double the capacity compared to the scenario with 100% MPR of HDVs.

Several studies also conducted field tests for the performance of the CACC system. Shladover et al., [284] tested the performance of the ACC and CACC vehicles by collecting and analyzing the field experiments data. Results showed that increasing the market penetration rate (MPR) of ACC vehicles would slightly increase the roadway

capacity. However, increasing CACC vehicles could significantly increase the roadway capacity. Milanés et al. [206] conducted a field trial of four vehicles equipped with the CACC system to exchange information. The result indicated that the CACC system needs less response time to the speed change of the leading vehicle. Hence, the CACC system could improve traffic/string stability with cooperative speed adjustment and less following gap. Another field trial of the CACC vehicles in the Connect and Drive project also suggested that vehicles with the CACC system could form a platoon of vehicles with a 0.7-second headway. This could significantly improve the string stability of the traffic flow [252].

B.1.4.2 Latitudinal Movement Control of CAVs

A safe, smooth, and efficient lane-changing behavior is essential for fulfilling the latitudinal movements of an AV. Several studies also proposed a specific lane-changing control model for AVs/CAVs. Nilsson et al. [229] proposed a pragmatic model to determine a safe following gap and time instance to perform the lane-changing maneuver. Field test results of the proposed model on a VOLVO V60 vehicle indicated a good performance of real-time ability, safety, and efficiency. Shi et al. [279] proposed a hierarchical reinforcement learning approach for modeling the automated lane-changing control process. The proposed approach could output the lane-changing decision and maneuver with the consideration of safety. Results indicated that the AV could smoothly and safely change to the target lane. Wang et al. [323] adopted deep deterministic policy gradient reinforcement learning to control continuous lane-changing behavior in dynamic driving situations. Simulation results showed the reinforcement learning agent vehicle could smoothly and stably change to the target lane under diverse driving environments.

B.1.5 Control Strategy for CAVs at Intersections

B.1.5.1 Signalized Intersection Control

Pre-timed Signal Control

Pre-timed signal control is a type of control where the signal cycle length, phase durations, and phase sequences are predetermined and fixed. Figure 50 shows a simple example of the pre-timed signal scheme for two phases, and the green time for each phase provided by traffic light controllers is fixed. As pre-timed signal control cannot compensate for temporal fluctuations in traffic flows, it is ideally suitable for intersections that have consistent traffic volumes and patterns on a daily or day-of-week basis [310].

It is noted that the traffic demands would be different during different periods, such as morning/evening peak hours vs. off-peak hours and weekdays vs. weekends. Neglecting differences of the hour-to-hour and day-to-day traffic demands would result in ineffective green time splits during the signal cycles and therefore can cause significant delays at intersections. Hence, several pre-timed signal schemes during the day would be necessary to introduce dynamic features for static traffic light controllers.

Pre-timed signal control does not need to install inductive loops, sensors, or cameras to obtain real-time traffic volume information on the intersection. This would save a significant amount of equipment and maintenance expenses. However, a lot of human efforts to measure traffic volume at different periods and calculate pre-timed schemes might be necessary to keep the pre-timed signal effective.

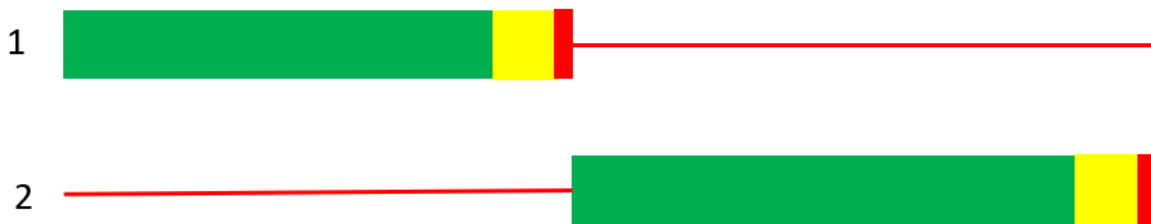


Figure 50. Pre-timed signal control scheme

Actuated Signal Control Different from the pre-timed signal control, the actuated signal control would control (called and extended) the phase duration by the real-time traffic information collected and provided by detectors (e.g., inductive loops or cameras). The phase duration is dynamically prolonged by detected traffic demands and predefined activation functions to better fit dynamic traffic conditions. The signal could also be actuated by the distance gaps or time gaps. The distance gap-based actuated traffic control is commonly utilized in Germany and could extend the green light phase if the gap between two vehicles is less than a certain value [40]. As long as the loop detector detects a continuous traffic stream (a sufficient time/distance gap between successive vehicles), then the

green duration would be extended until the maximum green time is reached. Similar to the distance gap-based actuated control, the time loss-based actuated control scheme could be triggered by the time loss of vehicles. However, this needs to capture traffic within an area of a lane or lanes, which is usually fulfilled by a vehicle tracking camera or several loop detectors.

As another simple example, Figure 51 illustrates the extension of the green light phase in an actuated signal scheme. The solid green represents the minimum green duration, and the light green represents the extension of the green time. Actuated control can be classified into semi-actuated and fully-actuated control based on the detected number of traffic demands/movements at an intersection.

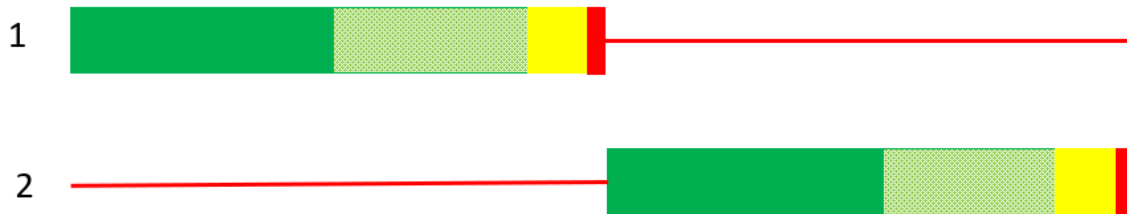


Figure 51. Actuated signal control scheme

Semi-actuated Signal Control: Semi-actuated signal control only detects part of traffic movements at an intersection. Usually, the inductive loops will be installed in the minor-road at the intersection. The phases for the major-road will sustain a green indication until the controller received a request for switching to the minor movement phase or the major movement phase reaches a maximum green time. Semi-actuated control is suitable for intersections with little crossroad traffic demands or intersections that are part of the arterial coordinated signal system [310].

The semi-actuated control can decrease the delay on the major-road during periods of light through movements compared to the pre-timed control. Also, it is highly cost-efficient with no need to install and maintain detectors on the major-road. However, continuous requests for the minor movement phases may also induce excessive delay to the through movements on the major-road if the maximum green duration and switching phase parameters are not appropriately set.

Fully-actuated Signal Control: Fully-actuated signal control refers to the control where all phases are actuated, and it is ideally suitable for isolated intersections where the daily traffic demands and patterns vary frequently [310]. Fully-actuated control could reduce the delay by frequently responding to the variations in traffic demands and patterns. Additionally, detected traffic information enables the controller to efficiently allocate the cycle time on a cycle-by-cycle basis. Moreover, the controller could skip a phase if there has no service request for the road. Then the controller would reallocate the unused time from a skipped phase to a subsequent phase. However, fully-actuated control requires the detection of all traffic movements at an intersection. Hence, the cost of fully-actuated control is higher than pre-timed or semi-actuated control because more detectors are required.

Adaptive Signal Control: When traffic conditions change, modifying the current signal schemes is needed to improve the intersection system performance. In adaptive signal control, signal adjustments are made based on the predicted traffic flow at downstream intersections. Accurate and comprehensive traffic detection systems are needed for an adaptive signal control system to detect upstream and/or downstream traffic conditions in a network. Then the traffic conditions (volume and location) will be predicted by a specific algorithm. The adaptive signal controller could calculate an optimized signal timing plan based on the predicted traffic volume. In this regard, the adaptive signal controller allows signal intersections to react to real-time traffic variations.

By adjusting the signal schemes to more align with real-time traffic conditions, the real-time traffic signal optimization calculated by the adaptive signal controller can decrease traffic delay, waiting time, and queuing length. Adaptive signal control could have a profound impact at intersections where daily traffic conditions change rapidly or randomly. As summarized by Urbanik et al. [310], adaptive signal control could improve the average performance metric of the intersection by 10% to 50%.

B.1.5.2 Autonomous Intersection Control

As summarized by Namazi et al. [219], several studies implemented rule-based, optimized, hybrid, and machine-learning methodologies to coordinate the movement of CAVs through intersections. For rule-based intersection control, CAVs cross the intersection based on a predefined rule, such as first-come-first-serve (FCFS), space-time reservation-based rule, and auction-based policy. Because of the computational simplicity of the rule-based

methods, several of them have been validated by field tests and have been implemented in real-time intersection management [196].

Dresner and Stone [79] proposed a centralized FCFS strategy for the intersection to determine the passing sequence of vehicles. The FCFS rule prioritizes the vehicle that arrives first at the stop line and does not consider the number of vehicles that arrived. This may decrease traffic efficiency and cause congestion at the intersection.

Additionally, Dresner and Stone [80] proposed an Autonomous Intersection Management (AIM) system for the efficient management of fully autonomous vehicles (Level 4 or 5) at intersections. The AIM is a multi-agent and reservation-based control system that outperforms conventional control systems (traffic lights and stop signs) in terms of delay and safety. However, the proposed AIM system needs a 90% market penetration rate of CAVs.

Vasirani and Ossowski [319] extended the works of Dresner and Stone [80] by combining the auction-based policy and reservation-based intersection control method. Compared to the FCFS-Light in the AIM system, the proposed approach decreased the probability of deadlock and reduced more than 70% of the average travel time.

B.1.6 Intersection Capacity Analysis Methods

B.1.6.1 Empirical Based Methods

Compared to the freeway system, traffic conditions in the intersection system are more complex as there have been many more conflict points and also different types of transportation users (vehicles, cyclists, and pedestrians). To analyze the impact of CAVs at intersections, the capacity (or throughput) of the intersection has been frequently utilized as a performance indicator in many previous studies. Generally speaking, there are two main ways to improve the throughput of the intersection:

- Increasing the number of vehicles that crossed the intersection during a time unit.
- Decreasing the average travel time for the vehicle to cross the intersection.

HCM's research work

Highway Capacity Manual [117] provided several empirical calibrated equations to calculate the capacity of conventional intersections considering different roadway, geometric, traffic, and control conditions. The capacity of the intersection could be modified by several adjustment factors. Also, the volume capacity ratio was implemented as a performance indicator for the intersection.

Brilon and Wu's research work

Brilon and Wu [41] developed a conflict-based technique to calculate the capacity of the unsignalized intersection. The proposed method simplified the theoretical structure of the conventional gap acceptance method. Based on the calibrated parameters, the proposed method could measure traffic performance such as capacity, average delay, and queue length.

Dahl and Lee's research work

Dahl and Lee [63] modified the gap acceptance method to estimate roundabout capacity by calibrating gap acceptance parameters for trucks and passenger vehicles separately. Results indicated that increasing the percentage of trucks would decrease the capacity of the intersection, and the modified model could calculate the capacity more accurately than the unmodified model.

Abhishek et al.'s research work

Abhishek et al. [39] improved the gap acceptance model to calculate unsignalized intersection capacity by incorporating driver impatience behaviors with merging behaviors. Also, the modified approach allowed different gap acceptance behaviors for different drivers or vehicles. Moreover, the modified model implemented a novel queueing model to calculate the mean service time, hence, facilitating the calculation of minor road capacity for an unsignalized intersection.

In summary, the capacity/throughput has been measured and served as a key performance indicator for the intersection. Table 22 exhibits several empirical-based methods that were proposed to measure the capacity of intersections.

B.1.6.2 Simulation Based Methods

Impacts of CAVs under 100% Market Penetrate Rates

Li et al.'s research work

Li et al. [172] jointly optimized signal timing and trajectories of the CAVs at an isolated intersection. Compared with a traditional actuated signal control scheme, the simulation results showed that the proposed control method could increase intersection throughput by 2.7–20.2% and reduce the average delay by 16.2–36.9% based on different traffic demands.

Abdelhameed et al.'s research work

Table 22. Summaries of empirical-based methods on intersection capacity analysis

No.	Reference	Intersection Type	Method	Capability of the Method
1	HCM, 2010	Signal/unsignalized Intersection, Roundabout	Empirical calibrated equations	·Considering different roadway, geometric, traffic, and control conditions
2	Brilon and Wu, 2001	Unsignalized Intersection	Conflict-based technique	·Simplifying the theoretical structure compared to gap acceptance method
3	Dahl and Lee, 2012	Roundabout	Modified gap acceptance method	·Calculating the capacity more accuracy than unmodified model
4	Abhishek et al., 2019	Unsignalized Intersection	Modified gap acceptance model	·Incorporating driver impatience behavior with merging behavior; ·Allowing different gap acceptance behaviors; ·Facilitating the calculation of minor road capacity for an unsignalized intersection

Abdelhameed et al. [13] utilized a hybrid fuzzy-genetic controller to minimize the travel time of CAVs while avoiding possible collisions at the intersection. Results indicated a 91% increase in throughput and about a 62–72% decrease in delay compared to the fixed traffic light controller and the un-optimized fuzzy logic controller.

Chen and Kang's research work

Chen and Kang [46] proposed a win-fit reservation management scheme for CAVs to cross an intersection without possible collisions. Results showed a reduction in trip delay by 31–95% compared with first-come-first-service and signal control schemes.

Liu et al.'s research work

Liu et al. [187] developed a trajectory planning approach for autonomous intersection management (TP-AIM). The proposed system assigned priority and collision-free trajectories to CAVs. Results indicated a 20% increase in the throughput of the intersection. Moreover, a 10% reduction in delay could be observed compared to a traffic light controller.

He et al.'s research work

He et al. [123] introduced a conflict-avoidance-based approach to coordinate CAVs at an unsignalized intersection with all-direction turn lanes. The simulation results indicated that the proposed approach outperformed traditional signal control by increasing 50% of the throughput and decreasing 60% of the travel time.

Wei et al.'s research work

Wei et al. [330] proposed a game theory method to maximize throughput and minimize the accidents and congestion of the CAVs at the intersection. A platoon formation model and a strategic game theory model were proposed to control CAV movements at the intersection. Results showed that the proposed control method could increase the throughput by 140% and 43% in light and heavy traffic demand conditions, respectively.

Sun et al.'s research work

Sun et al. [291] developed a MCross scheme to maximize intersection capacity with CAVs. Several simulation examples indicated that the proposed scheme could almost double the intersection capacity (i.e., by 99.51%) compared to a signal control scheme.

In summary, several studies designed an intersection control system that assumed 100% market penetration rate (MPR) of CAVs so that vehicles could obtain full information and be controlled by the system controller [108]. Table 23 exhibits a summary of the studies on simulation-based intersection capacity analysis with 100% MPR of CAVs.

Impacts of CAVs under Mixed Traffic Environment

Several proposed intersection control systems require a modification of the existing intersection systems, and several of them require high market penetration rates (MPRs) of AVs or CVs [18, 80]. Reconstruction of those intersections or installing the V2I equipment would take a long time. Hence, it is reasonable to expect for a longer time for AVs to achieve high MPRs or be fully applicable in those intersection systems.

Additionally, several studies pointed out that a significant improvement in the system performance requires a certain MPR of the CAVs. Arnaout and Arnaout [26] utilized simulations to investigate the effects of the CACC-equipped CAVs on the traffic flow on a multilane highway. Results showed that low MPRs of CACC-equipped CAVs would have a slight impact on the traffic flow.

Shladover et al.'s research work

Shladover et al. [284] indicated that a 40% market penetration rate (MPR) of CACC-equipped vehicles is

Table 23. Summaries of capacity analysis studies of CAVs under 100% market penetrate rate

No.	Reference	Aim and method	Criteria	Main result
1	Li et al., 2014	Optimize signal timing and trajectories	Throughput, Delay	Increase intersection throughput by 2.7–20.2% compared with actuated signal control
2	Abdelhameed et al., 2015	Minimize the travel time of CAVs while avoiding possible collisions	Throughput, Delay	Increase throughput by 91% compared to the fixed traffic light controller and the un-optimized fuzzy logic controller
3	Chen and Kang, 2016	Conflict-avoidance-based approach to coordinate CAVs	Delay	Reduce trip delay by 31%-95% compared with FCFS and signal control schemes
4	Liu et al., 2018	Assign priority and collision-free trajectories to CAVs	Throughput, Delay	Increase throughput by 20% compared to signal control scheme.
5	He et al., 2018	Conflict-avoidance-based approach to coordinate CAVs	Throughput, Travel time	Increase throughput by 50% compared to signal control scheme
6	Wei et al., 2018	Game theoretic framework to maximize throughput and minimize the accidents and congestion of the CAVs	Throughput	Increase the throughput by 140% and 43% in light and heavy traffic demand conditions, respectively
7	Sun et al., 2018	MCross scheme to maximize intersection capacity	Throughput	Almost double the intersection capacity by 99.51% compared to signal control scheme

a critical threshold to achieve a 10% improvement of the roadway capacity. Also, 100% MPR of CACC-equipped vehicles could double the capacity compared to the scenario of 100% MPR of HDVs.

Lee and Park's research work

Lee and Park [160] proposed a cooperative vehicle intersection control system to remove signals while guaranteeing the safety of CVs. Simulation on a four-way single-lane approach intersection with the proposed system indicated that the throughput and total travel time were improved by 8% and 33% compared to an actuated signal control system.

Jiang et al.'s research work

Jiang et al., [139]) utilized an optimization method to control the speed of CAVs at an isolated intersection. Results indicated that benefits grow with the MPRs of CAVs until they level off at about 40% MPR. Also, with a 60% MPR of CAVs, the throughput of the intersection would be improved by 7.06% and 10.80% under saturated flow rate ($v/c = 1$) and oversaturated flow rate ($v/c = 1.2$) conditions, respectively.

Sharon and Stone's research work

Sharon and Stone [278] proposed a hybrid autonomous intersection management (H-AIM) system to accommodate mixed traffic conditions. H-AIM could identify approaching HDVs by sensor technologies. Compared to the basic AIM system, the H-AIM can improve the throughput and delay with only a 10% market penetration rate of CAVs. With a 50% MPR of CAVs, the H-AIM can increase the throughput of a four-way intersection and a three-way intersection by 10% and 6%, respectively.

Algomaiah and Li's research work

Algomaiah and Li [18] proposed a first-come-first-serve reservation-based system at the intersection with different MPRs of CAVs. Simulation results indicated that the proposed control system outperforms traffic signals after a 75% MPR of CAVs. Additionally, the proposed system would increase the throughput by 50% with a 100% MPR of CAVs compared to a signal control system.

In summary, simulation-based models were frequently utilized to evaluate the impacts of AV/CAV technologies on the intersection capacity/throughput. Table 24 summarizes previous capacity analysis studies on intelligent vehicles at intersections considering different MPRs. Additionally, Table 25 summarizes previous studies which utilized other performance criteria to evaluate the impacts of intelligent vehicles at intersections considering different MPRs. The evaluation criteria for the performance of CAVs at the intersection mainly included efficiency (delay, travel time, speed, throughput, density, queuing length), safety (collision avoidance, resolving conflict), and ecology (energy/fuel consumption, emission).

Table 24. Summaries of capacity studies of CAVs under mixed traffic environment

No.	Reference	Veh.	Object and method	Software	Criteria	Main result
1	Shladover et al. 2012	HDTV, CV, AV, CAV	Simulation ACC and CACC based on field experiment data (for time gap settings) to estimate the effect on roadway capacity	AIMSUN	Capacity	· 40% market penetration rate (MPR) of CACC equipped vehicles is a critical threshold to achieve a 10% improvement of the capacity. · 100% MPR of CACC-equipped vehicles could double the capacity
2	Lee and Park, 2012	CV	Cooperative Vehicle Intersection Control	VISSIM	Through-put, Delay, Emission	· The throughput and total travel time were improved by 8% and 33% compared to actuated signal control system
3	Jiang et al., 2017	CAV	Optimizing speed of CAVs	VISSIM, Matlab	Fuel, CO ₂ , Through-put	· Benefits grow with the MPRs of CAVs until they level off at about 40% MPR.
4	Sharon and Stone, 2017	CAV	Hybrid autonomous intersection management	SUMO	Queue length, Through-put	· H-AIM can decrease delays for AVs even at a 1% MPR. · With 50% MPR of CAVs, increase the throughput for four-way intersections and three-way intersections by 10% and 6%, respectively.
5	Algomaiah and Li, 2019	CAV	A first-come-first-serve reservation at intersection	VISSIM	Through-put, delay	· The proposed control system outperforms traffic signals after a 75% MPR of CAVs.

Microscopic simulation software has been widely used in previous studies, such as VISSIM, SUMO, and AIMSUN, which are generally integrated with MATLAB and JAVA. It is noted that most studies indicated a positive effect of intelligent vehicles, while some others found that the intelligent vehicles could improve the system performance only after certain MPRs [18, 139, 161]. Moreover, several studies found that the interaction between intelligent vehicles with HDVs would result in a negative impact on system performance [81]. This is in line with the phenomenon that low MPRs of intelligent vehicles would decrease system performance [320, 339].

B.1.7 Intersection Modeling Scenarios and Parameters /

Jiang et al. [139] utilized an optimization method to control the speed of CAVs at an isolated single-lane intersection. With a 60% MPR of the CAVs, simulation results indicated that the intersection throughput would be improved by 7.06% and 10.80% under saturated flow ($v/c = 1$) and over-saturated flow ($v/c = 1.2$) conditions, respectively.

Sharon and Stone [278] proposed a hybrid autonomous intersection management (H-AIM) system. The performance of the system was tested by the simulations at a four-way intersection and a three-way intersection. Compared to the basic AIM system, the H-AIM can improve throughput and delay with only a 10% MPR of CAVs. With a 50% MPR of CAVs, the H-AIM can increase the throughput for four-way intersection and three-way intersection by 10% and 6%, respectively.

Yang et al. [339] proposed an eco-CACC system to compute optimal fuel consumption trajectories for CACC-equipped CAVs. When vehicles are traveling at signalized single-lane and multi-lane intersections, the increase of MPRs of CACC vehicles would decrease fuel consumption and air pollution correspondingly. The proposed system could save about 40% of the fuel consumption with a 100% market penetration rate of eco-CACC vehicles. Moreover, when vehicles were traveling at a multi-lane intersection, the proposed system would increase fuel consumption if the MPRs of eco-CACC vehicles are over 30%.

Sun et al. [291] developed an intelligent intersection system with continuous flow design and tandem control to maximize the intersection capacity with CAVs. Numerical examples for unbalanced flow, heavy left-turn traffic, heavy conflicting movements, and all demands flow cases were tested. Simulation results indicated that the proposed scheme could almost double the intersection capacity compared to a signal control scheme.

He et al. [123] introduced a conflict-avoidance-based approach to coordinate CAVs at an unsignalized intersection with all-direction turn lanes. The traffic demands per lane were increased from 100 to 1000 veh/hr. The simulation results indicated that the proposed approach outperformed traditional traffic lights by increasing 50% of the throughput and decreasing 60% of the travel time.

Table 25. Summaries of other performance measures of CAVs under mixed traffic environment

No.	Reference	Veh.	Object and method	Software	Criteria	Main result
1	Lee et al., 2013	CV	Cumulative travel-time responsive (CTR) real-time intersection control	VISSIM, Matlab	Delay, speed	· The CTR algorithm improves the system performance after a 30% MPR of CVs. · CTR algorithm outperformed the actuated controls after a 70% MPR of CVs.
2	Guler et al., 2014	CV	Optimizing the departure sequences	Matlab	Delay	· CVs with MPRS from 0% up to 60% can significantly reduce the average delay. · The average delay could be significantly reduced even with low MPRS (20–40%).
3	Yang et al., 2016	CV, AV	Optimization of departure sequence and trajectory by maximizing the speed entering the intersection	Java	Stops, Delay	· This algorithm performs better than the actuated signal control after a 50% MPR of CVs. · Even a 50% information level for CVs could significantly decrease the delay and stops.
4	Yang et al., 2017	CAV	Eco-CACC system that computes the fuel-optimum vehicle trajectory	Integration	Fuel	· Eco-CACC system produces vehicle fuel savings up to 40% at a 100% MPR of CAVs. · Lower MPRS of CAVs increase fuel consumption on multi-lane roads, and the system decreases the fuel consumption only after a 30% MPR of CAVs.
5	Du et al., 2017	CV	Coordinate CVs at adjacent signalized intersections.	–	Fuel	· Increasing the MPRS of CVs would decrease fuel consumption. · Fuel consumption will increase if the CV is following an HDV.
6	Pourmehrab et al., 2018	AV	Headway minimization	Matlab	Travel Time	· The average travel time decreases with higher MPRS of AVs.
7	Zhao et al., 2018	AV	Minimize the fuel consumption for platoons	Matlab	Fuel, Travel time	· Both fuel consumption and travel time decrease with the increasing MPRS of AVs. · The benefits of cooperation between AVs and HDVs are most evident for lower MPRS, and a platoon size of 5 can reduce 22% fuel consumption under a 60% MPR of AVs.
8	Liang et al., 2019	CV, AV, SGV	Jointly optimizing the signal phase and timing plan along with speed guidance	Java	Delay, stops	· The average delay and number of stops decrease with higher MPRS of CV, AVs, and SGVs (HDV with speed guidance-enabled vehicles). · The marginal benefits decrease rapidly when MPRS of the CVs exceed 40%.
9	Virdi et al., 2019	CAV	Safety assessment of mixed flow	VISSIM	Conflicts	· CAVs at low penetration rates increase conflicts at signalized intersections while decreasing conflicts at priority-controlled intersections.

Table 26. Summaries of intersection modeling scenarios with CAVs

No.	Reference	Intersection Type	Scenarios	Findings
1	Jiang et al., 2017	Single lane signalized intersection	Mixed flow; Traffic demands: non-saturated ($v/c = 0.5$), saturated ($v/c = 1$), oversaturated ($v/c = 1.2$)	· Increase the throughput by 7.06% and 10.80% with 60% MPR of CAVs under saturated ($v/c = 1$) and oversaturated ($v/c = 1.2$) conditions, respectively
2	Sharon and Stone, 2017	A four-way intersection and a three-way intersection	Mixed flow; Traffic demands from low to high (150 - 750 vehicles/hour/lane)	· With 50% MPR of CAVs, the H-AIM can increase the throughput for four-way intersection and three-way intersection by 10% and 6%, respectively.
3	Yang et al., 2017	Single lane and multilane signalized intersections	Mixed flow	· Increase the fuel consumption if the MPR of eco-CACC vehicles are over 30%
4	Sun et al., 2018	An intersection with continuous flow design and tandem control	Unbalanced flow, heavy left-turn traffic, heavy conflicting movements, all demand flow cases	· Increase intersection capacity by 99.51% compared to signal control
5	He et al., 2018	Unsignalized intersection with all-direction turn lanes	Increase traffic demands from 100 – 1000 (vehicles/hour/lane)	· Increase 50% of the throughput compared to signal control scheme
6	Algomaiah and Li, 2019	Next-generation interchange with different combinations of dedicated and shared lanes	Mixed flow; Communication range (600, 800, 1000 ft); Traffic demands from 400 to 1000 vehicles/hour/lane	· Increase about 50% of the throughput with 100% MPR of CAVs compared to signal control scheme; · 800 ft communication range shows a relatively lower delay

Algomaiah and Li [18] proposed a first-come-first-served reservation-based system at the intersection considering different MPRs of CAVs. The geometrical designs of the intersection included different combinations of dedicated and shared lanes. Traffic demands from 400 to 1000 vehicles/hour/lane and three communication ranges (600, 800, 1000 ft) were tested in simulations. Throughput and delay results indicated that the proposed control system outperformed a traffic signal scheme after a 75% MPR of CAVs.

In summary, Table 26 exhibits several intersection modeling scenarios using simulation methods to analyze the impacts of CAVs. Note that the following parameters were used in the simulation models for CAVs with the CACC system [206, 208, 337].

- Minimum gap when the vehicle is stopped (m)
- Maximum acceleration (m/s^2)
- Maximum deceleration (m/s^2)
- The maximum deceleration in case of emergency (m/s^2)
- Desired headway (s)
- Speed control factor
- Reaction time (s)
- The driver imperfection [0, 1]
- The control gain determining the rate of speed deviation (for Speed control mode)
- The control gain determining the rate of positioning deviation (for Gap closing control mode, Gap control mode, and Collision avoidance mode, respectively)
- The control gain determining the rate of the positioning deviation derivative (for Gap closing control mode, Gap control mode, and Collision avoidance mode, respectively)

B.1.8 Summary

This chapter summarizes a comprehensive review of the current state-of-the-art and state-of-the-practice on studies related to connected vehicles, autonomous vehicles, and connected and autonomous vehicles. Deployment and market penetration rate prediction, traffic flow control strategy for CAVs, the intersection control strategy for CAVs, intersection capacity analysis methods (empirical-based and simulation-based methods), and intersection modeling scenarios and parameters of CAVs are introduced and reviewed. This chapter is intended to provide a fundamental and

solid reference to develop control strategies for CAVs at the intersection, and conduct effective simulation strategies and impact analysis for future tasks.

B.2 IDENTIFYING POTENTIAL INTERSECTIONS

B.2.1 Introduction

As discussed in the literature review section in Chapter B.1, this chapter will identify potential intersections and collect necessary data related to selected intersections. Based on the literature review part, a hypothetical isolated four-way intersection will be tested as a basic scenario later. Also, a set of real-world intersections in North Carolina will be selected with different scenarios, including one isolated intersection and two adjacent intersections.

The following sections are organized as follows. Section B.2.2 presents the information on a hypothetical isolated four-way intersection. Section B.2.3 provides potential intersections in North Carolina with necessary data that are related to the pre-timed signal schemes. Finally, section B.2.4 concludes this chapter with a summary.

B.2.2 Typical Isolated Intersection Scenario

In this section, a hypothetical isolated four-way intersection (cross-intersection) is proposed to define a basic scenario for the simulation. This intersection will also be tested with different MPRs of CAVs. The results of these scenarios will be further tested in real-world intersections. This isolated intersection is introduced in this section.

B.2.2.1 Intersection Layout

As shown in Figure 52 the isolated intersection has four two-way approaches. The angle of the intersection is vertical. Also, the entrance and exit of each approach have three lanes. Each entrance (or inlet) has one lane for left-turn-only traffic, one lane for through-only traffic, and one lane for through and right-turn traffic.

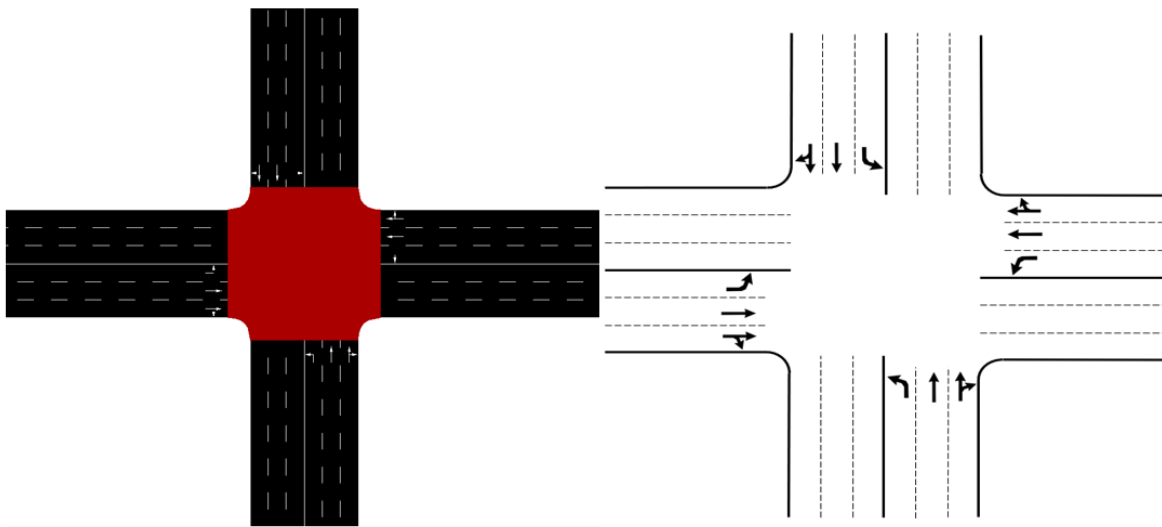


Figure 52. Layout of the hypothetical isolated four-way intersection

B.2.2.2 Pre-timed Signal Schemes

Pre-timed signal control is a type of control where the signal cycle length, phase durations, and phase sequences are predetermined and fixed. A pre-timed signal scheme is utilized in the hypothetical isolated intersection. The capacity of the intersection could be calculated based on the Highway Capacity Manual [117]. The maximum throughput could also be determined by the simulation method. As shown in Figure 53, eight potential signal phases are usually selected to accommodate different traffic volume scenarios.

B.2.2.3 Potential Traffic Demands

For hypothetical isolated four-way intersection scenarios, different traffic demands for each direction will be considered. Under a specific pre-timed signal scheme, the capacity of the intersection will be calculated based on the empirical-based method introduced by the Highway Capacity Manual [117]. Then the maximum throughput will be calculated with 100% MPRs of HDVs based on the simulation method. Moreover, to investigate the impact of CAVs on the traffic flow, different MPRs of CAVs will be considered during the simulation (increase from 0% to 100% by 25% per step). Then the maximum throughput under different MPRs of CAVs will be recalculated by the simulation

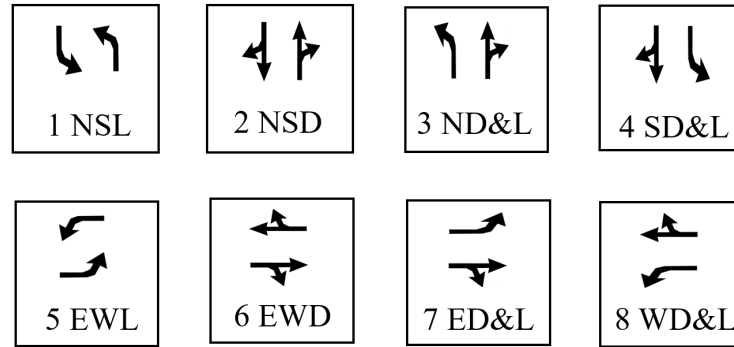


Figure 53. Potential signal phase of the intersection method. Following are the steps to determine potential traffic demands for the hypothetical isolated intersection.

- Calculate the capacity with a pre-timed signal scheme by the empirical method.
- Calculate the maximum throughput of the intersection by the simulation method.
- Determine the traffic demands based on the maximum throughput.
- Determine the volume of the CAV based on the market penetration rate of the CAV.

B.2.3 Potential Intersections in North Carolina

The selected intersections for the case study should be a typical intersections, and the results of the case study should be representative and could be transferred into other similar cases. Based on the distance between two intersections, an isolated intersection is defined when there has no adjacent intersection within one mile. To identify the impacts of CAVs on the intersection systems, the selected intersections contain two kinds of configurations, including an isolated four-way intersection and two adjacent intersections. The isolated four-way intersection is located in the city of Charlotte, NC. The two adjacent intersections are located between downtown Greensboro and the campus of the NCAT. The results of this research could be valuable to Project 3 as a feasibility study that will be conducted for using CAVs to connect NCAT's campus to downtown Greensboro sites. The peak-hour traffic volume data and pre-timed signal schemes are collected from the NCDOT database.

B.2.3.1 One isolated intersection in Charlotte, NC

As shown in Figure 54, the isolated intersection is the cross-section of N. Tryon Street and W. T. Harris Boulevard in the city of Charlotte, NC. The speed limit of the study site is 45 miles/hour.

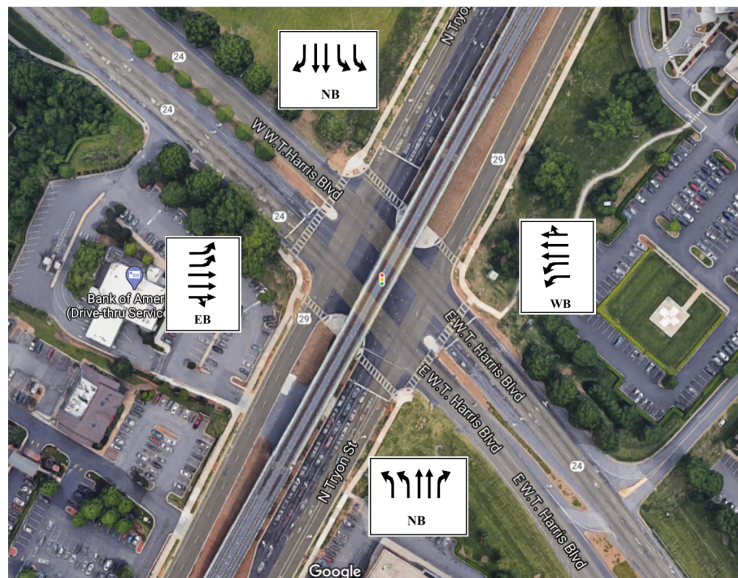


Figure 54. Isolated intersection in the city of Charlotte, NC

B.2.3.2 Two adjacent intersections in Greensboro, NC

The two adjacent intersections are located between downtown Greensboro and the campus of the NCAT. As shown in Figure 55, the distance between the two intersections is about 355 ft. The speed limits for the two adjacent intersections are both 35 miles/hour. For the minor streets, both Market St. and Friendly Ave. are one-way roads. The detailed layouts of two adjacent intersections are shown in Figure 56 and Figure 57.

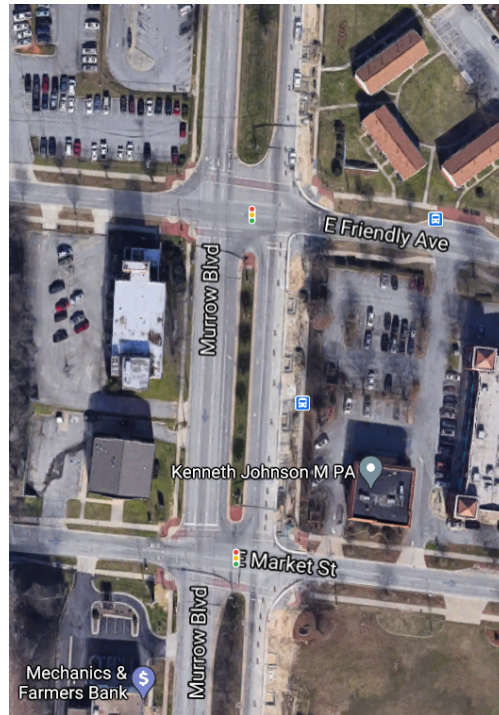


Figure 55. Two adjacent intersections in Greensboro, NC

B.2.4 Summary

In this chapter, a hypothetical isolated four-way intersection is proposed to set a basic scenario for the simulation. After that, one isolated intersection and two adjacent intersections in North Carolina are selected as potential case study scenarios. The layout, speed limits, peak-hour traffic volume, and pre-timed signal schemes of the intersection are all introduced. One isolated intersection and two adjacent intersections are selected as they could give representative results of the impact of CAVs on the intersection capacity. Also, two adjacent intersections are located between the downtown of Greensboro and the campus of the NCAT. Investigating these two adjacent intersections could give potential insights to Project 3 (which will be conducted by using CAVs to connect NCAT's campus to downtown Greensboro sites). This is basic preparation for simulating intersection capacity with CAVs in future tasks. All scenarios will be tested later with different MPRs of CAVs to investigate the potential impacts of CAV technologies on the intersection system.

B.3 DESIGNING SCENARIOS FOR CONDUCTING SIMULATION

B.3.1 Introduction

As discussed in the potential intersections conducted in Chapter B.2, this chapter will design specific scenarios for each intersection and collect necessary settings for conducting the simulations. In this part, a hypothetical isolated four-way intersection is selected as a basic scenario. An initial pre-timed signal scheme will be calculated for this typical intersection. Also, the intersection capacity will be calculated based on the empirical methods. Meanwhile, scenarios with different traffic demands and MPRs of CAVs will be tested in this typical intersection by applying micro-simulation methods. Moreover, two types of real-world intersections in North Carolina, including one isolated intersection and two adjacent intersections, will also be tested to analyze the impacts of CAVs on the intersection system performance.

The following sections are organized as follows. Section B.3.2 presents the empirical method for intersection

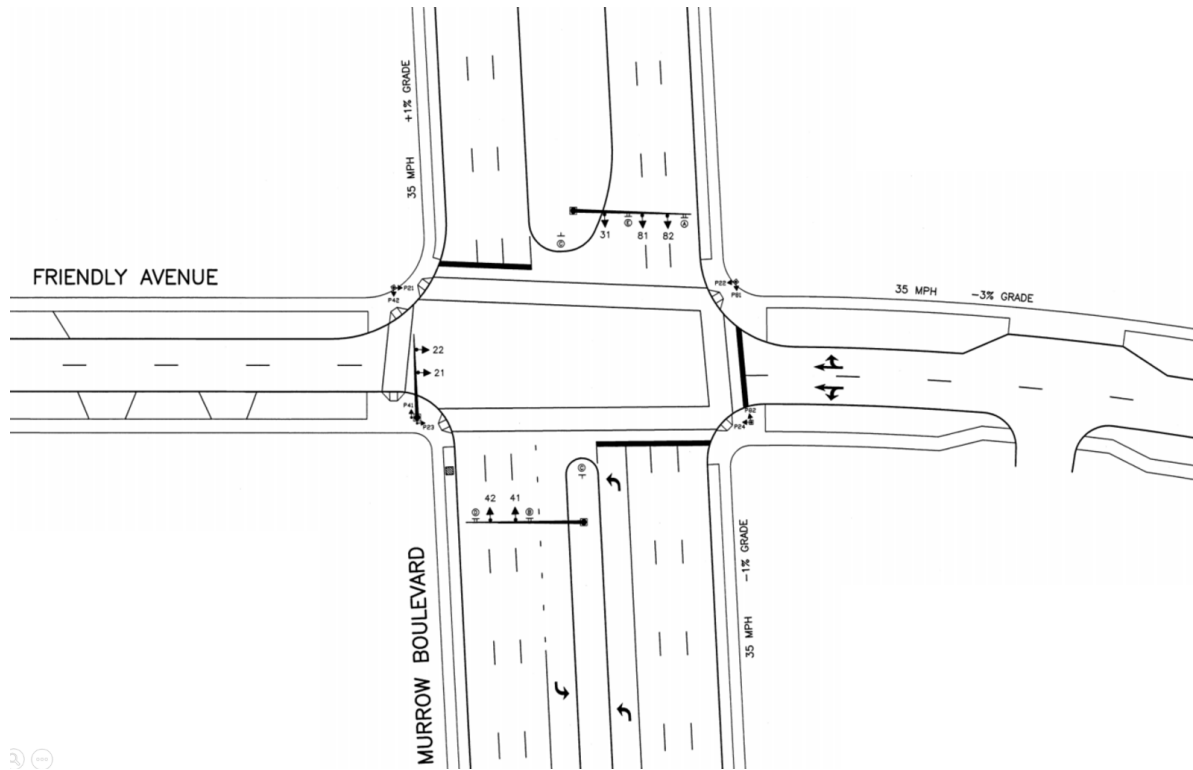


Figure 56. Layout of the first intersection (Friendly Ave. & Murrow Blvd.)

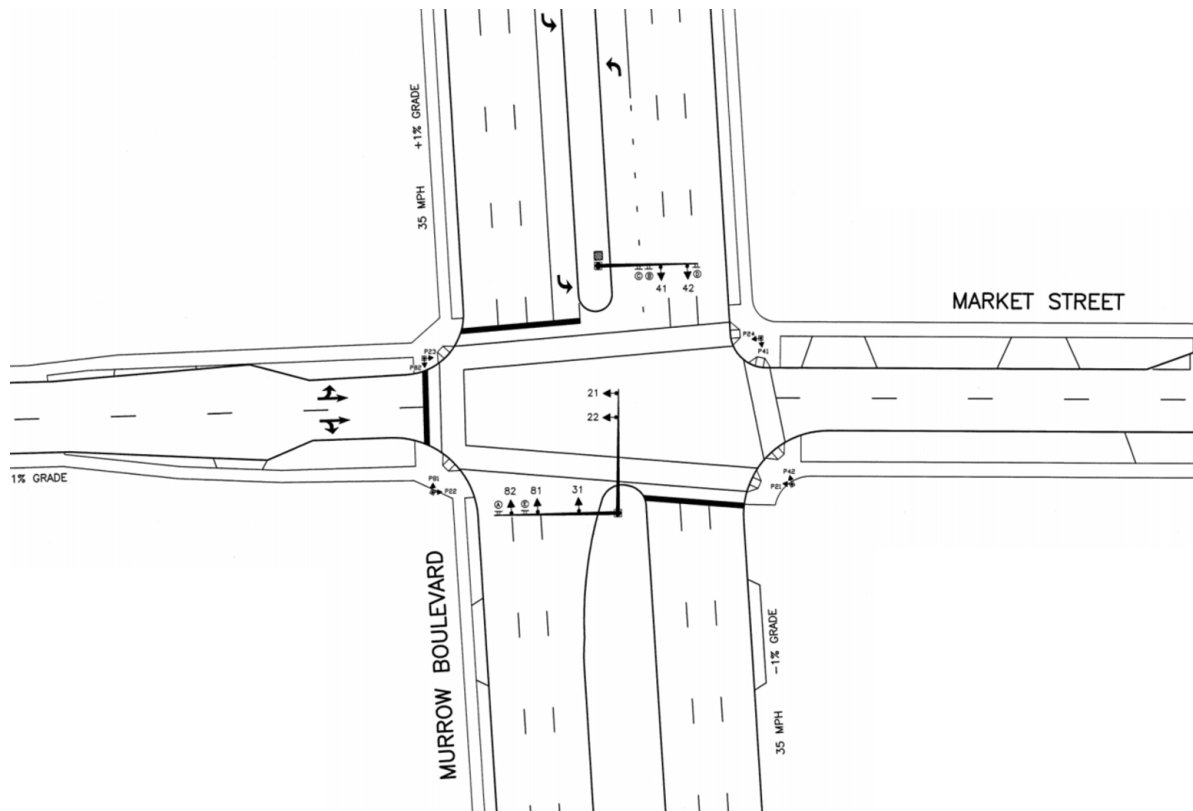


Figure 57. Layout of the second intersection (Market St. & Murrow Blvd.)

capacity analysis. Section B.3.3 introduces the microscopic simulation models for HDVs and CAVs. Section B.3.4 provides specific scenarios for a typical isolated intersection and two real-world intersections in NC. Finally, section B.3.5 concludes this chapter with a summary.

B.3.2 Empirical Method for Intersection Capacity Analysis

B.3.2.1 Quick-Estimation Method

The empirical method for intersection capacity calculation is based on the first five-step of the Quick-Estimation Method (QEM) that was introduced in the 2010 Highway Capacity Manual [117]. The HCM defines capacity as the maximum number of vehicles that can pass through the intersection under certain traffic, roadway, and signalization conditions during a 15-min period. The QEM determines the critical movements based on the signal phases and calculates the critical phase volumes. Then the intersection capacity is calculated based on the maximum traffic volume that the intersection could accommodate in an hour. Figure 58 provides the first five-step of the QEM.

- Step 1: Identify intersection traffic movements, number of lanes, and calculate hourly traffic volumes per lane. Usually, the hourly traffic volumes are modified to represent the peak 15-minute period.
- Step 2: Design a signal phasing plan and determine the traffic movements in each phase. Each phase usually accommodates two nonconflicting movements. The treatment (protected, permitted, etc.) of each left-turn movement is determined mainly based on the left-turn volume and the opposing through traffic volume.
- Step 3: Determine the critical volume per lane group that must be accommodated for each phase. The lane group is divided by the traffic movements in each phase. For example, the exclusive left-turn lane with a protected left-turn phase is usually designated as a specific lane group. The critical movement volume determines the amount of green time that should be assigned to the phase on one signal cycle.
- Step 4: Sum the critical phase volumes per phase to determine the overall critical volume that the intersection needs to accommodate.
- Step 5: Calculate the overall intersection capacity by determining the maximum critical volume that the intersection can accommodate per cycle. The maximum critical volume is determined by the saturated traffic flow. For signal lane cross-intersection, the HCM QEM recommended 1,710 vph for most purposes.

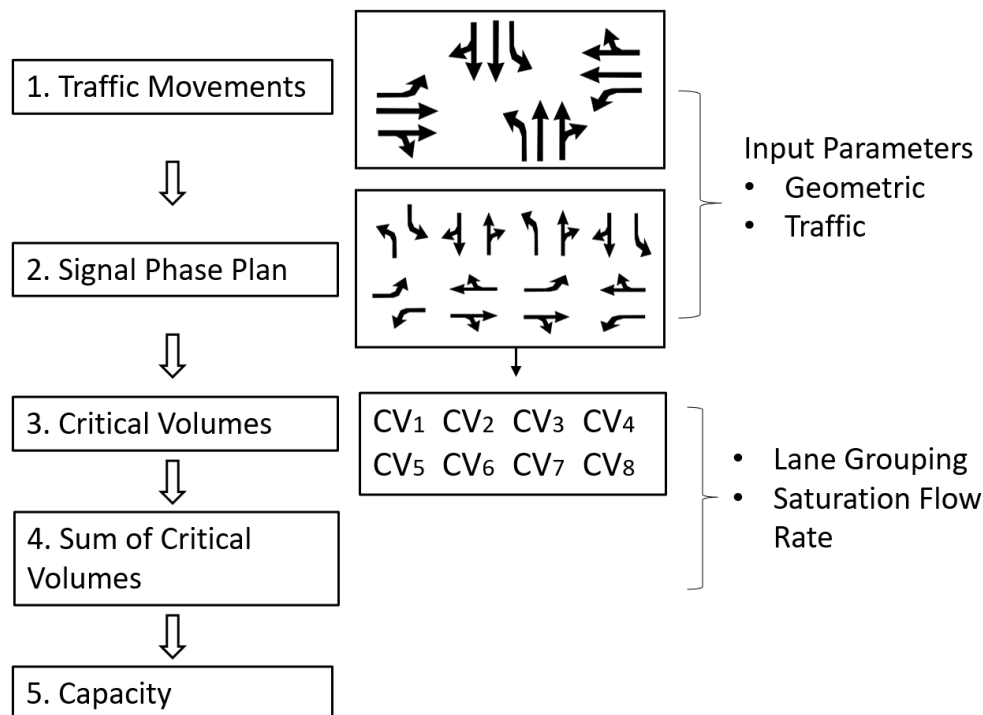


Figure 58. Illustration of the Quick Estimation Method framework for capacity estimation

B.3.2.2 Intersection Capacity Calculation

To determine the capacity of the intersection, the saturation flow of the lane group in each phase should be

first calculated. The saturation flow s_o of a lane is the maximum traffic that the lane could accommodate per hour,

$$s_o = 3600/h \quad (\text{B.1})$$

where, h denotes the average headway of the traffic, s .

HCM 2010 usually recommended a base saturation flow rate, i.e., 1,900 passenger cars per hour per lane (pc/h/ln). The saturation flow rate of the lane group capacity is usually adjusted for a variety of conditions,

$$s = s_o N f_w f_{HV} f_g f_p f_{bb} f_a f_{LU} f_{LT} f_{RT} f_{Lpb} f_{Rpb} \quad (\text{B.2})$$

where s is the saturation flow rate (or Capacity) of the lane group, veh/hr. s_o indicates the base saturation flow rate per lane, pc/h/ln. N denotes the number of lanes in the lane group. The adjustment factors f (e.g., lane width, grade, parking, pedestrians) are specified in HCM 2010 [117].

For each lane group at a signal intersection, the lane group capacity is computed as the product of the adjusted saturation flow rate and effective green time per cycle ratio. Then the signal intersection capacity is expressed as an hourly rate, with units of vehicles per hour. The capacity of the signal intersection is the sum of the lane group capacity,

$$c = \sum_i s_i \frac{g_i}{C} \quad (\text{B.3})$$

where c indicates the capacity of the signal intersection. s_i expresses the saturation flow rate for all lanes in lane group i . g_i/C is the effective green time per cycle ratio for lane group i .

The intersection signal phase must be timed to accommodate the most intense traffic movements. An initial pre-timed signal plan could be calculated as follows.

Step 1 Develop a basic phase plan.

Step 2 Convert all traffic volumes to through vehicle equivalents.

Step 3 Determine critical lane volumes.

Step 4 Determine Yellow and All-Red Intervals.

Step 5 Determine lost time.

Step 7 Allocate effective green time to each phase.

First, the maximum sum of critical lane volumes V_C is given as,

$$V_C = \frac{1}{h} \left[3,600 - N t_L \left(\frac{3,600}{C} \right) \right] \quad (\text{B.4})$$

where N indicates the number of phases. t_L is the total time loss in one phase. C is the cycle length.

For the total lost time per phase,

$$t_L = l_1 + l_2 \quad (\text{B.5})$$

where, l_1 denotes the start-up lost time, i.e., additional time for each initial headway. l_2 indicates the clearance lost time, i.e., the time between the front wheel of the last pass vehicle crossing the stop line and the start of green for the next phase. The recommended value for t_L is 4 s. Meanwhile, the effective green time g_i , i.e., the amount of time that vehicles can move in one phase, is given as,

$$g_i = G_i + Y_i - t_{Li} \quad (\text{B.6})$$

where G_i denotes the actual green time for movements i . Y_i is the sum of yellow and all red time for movements i , $Y_i = y_i + ar$, y_i is yellow time, ar is all-red time. t_{Li} indicates the total lost time for movements i .

The allocation of the effective green time G_i to each phase is based on the critical volume to the maximum sum of critical volume ratios,

$$G_i = (C - N t_L) \frac{C V_i}{V_C} \quad (\text{B.7})$$

where C is the cycle length. N is the total number of the phase. t_L is the total time loss per phase. $C V_i$ is the critical volume for phase i . V_C is the sum of critical volume in one signal cycle.

B.3.3 Microscopic Simulation Model for Human Driving Vehicles

The microscopic simulation method is implemented in this research to investigate the impacts of CAVs on the intersection capacity. The main difference in microscopic simulation models of the HDVs and CAVs is the control

mode of longitudinal movements (which mainly controls the travel speed), acceleration/deceleration, and car following gaps between vehicles. In this research, The IDM is implemented for modeling HDVs. The ACC system is utilized to model CAVs when the CAV is following a HDV. The CACC system is implemented to model CAVs when the CAV is following a CAV. The longitudinal movement controls of the CAVs are expected to significantly improve the efficiency of the roadway/intersection systems.

B.3.3.1 Traffic Simulation Model for Human Driving Vehicles Intelligent Driving Model

The IDM is implemented for HDVs according to Treiber et al. [306]. The IDM calculates the acceleration rates of the subject vehicle by balancing the ratio of the current velocity versus the desired speed minus the ratio of the desired gap versus the current gap with respect to the preceding vehicle [306].

$$a_{i,k} = a_{\max} \left[1 - \left(\frac{v_{i,k}}{v_d} \right)^\delta - \left(\frac{s^*(v, \Delta v)}{s_{i,k}} \right)^2 \right] \quad (\text{B.8})$$

$$s^*(v_{i,k}, \Delta v) = s_0 + \max \left[0, \left(v_{i,k} t_d + \frac{v, \Delta v}{2\sqrt{a_{\max} d_c}} \right) \right] \quad (\text{B.9})$$

where $a_{i,k}$ denotes the acceleration of the subject vehicle i in time step k . $a_{\max}$ represents the maximum acceleration allowed; $v_{i,k}$ is the current speed of the subject vehicle. v_d is the desired speed. δ represents the acceleration exponent. $s^*(v, \Delta v)$ denotes the desired minimum gap. (Δv) represents the speed difference between the subject vehicle and the preceding vehicle. $s_{i,k}$ is the current distance to the preceding vehicle. s_0 represents the linear jam distance. s_1 denotes the non-linear jam distance. t_d denotes the desired time gap. d_c is the comfortable deceleration.

Traffic Simulation Models for Connected and Autonomous Vehicles The ACC system and CACC system are utilized for CAV simulation according to previous works [187, 337]. When the CAV is following a HDV, then the car-following system is changed into the ACC mode. When the CAV is following a CAV, then the car-following system is switched into the CACC mode for a closer car-following behavior.

Adaptive Cruise Control

The ACC system, which is a variant of the IDM, is proposed and dynamically controlled by four modes, i.e., cruising control, gap control, gap-closing control, and collision avoidance mode [206, 208, 337].

Cruising control mode: The cruising controller of the ACC system is triggered if there are no preceding vehicles within the range of 120 m covered by the sensors [187, 337]. This controller aims to keep the ACC vehicle traveling at a desired speed.

$$a_{i,k+1} = k_1 (v_d - v_{i,k}) \quad (\text{B.10})$$

where $a_{i,k+1}$ represents the acceleration recommended for the i -th subject vehicle at the time step $k+1$; v_d denotes the desired speed; $v_{i,k}$ indicates the speed of the subject vehicle i at the current time step k , and k_1 denotes the control gain parameter determining the acceleration by the speed deviation. Typical values for k_1 range between 0.3 to 0.4 s^{-1} in [337], and this study selects 0.4 s^{-1} for k_1 .

Gap control mode: The gap control mode of the ACC system is triggered when the gap and speed deviation with respect to the preceding vehicle are less than 0.2 m and 0.1 m/s , respectively [337]. The acceleration of the subject vehicle i at the next time step $k+1$ is calculated based on the gap and speed deviations.

$$a_{i,k+1} = k_2 s_{i,k} + k_3 (v_{i-1,k} - v_{i,k}) \quad (\text{B.11})$$

where $s_{i,k}$ denotes the gap deviation of the subject vehicle i at the current time step k . $v_{i-1,k}$ represents the current speed of the preceding vehicle (index in $i-1$); k_2 and k_3 denotes the control gains on the gap and speed deviations, respectively. Typical values for the optimal gains are $k_2 = 0.23 \text{ s}^{-2}$ and $k_3 = 0.07 \text{ s}^{-1}$ [337].

The gap deviation of the subject vehicle is defined according to [206].

$$s_{i,k} = x_{i-1,k} - x_{i,k} - d_0 - t_d v_{i,k} \quad (\text{B.12})$$

where $x_{i-1,k}$ and $x_{i,k}$ represent the current positions of the preceding vehicle and the subject vehicle, respectively. $v_{i,k}$ is the current speed of the subject vehicle. t_d indicates the desired time gap for the ACC vehicle.

Gap-closing control mode: The gap-closing control mode was proposed in [207] and is activated when the gap to the preceding vehicle is smaller than 100 m . When the gap is between 100 m and 120 m , the subject vehicle

Table 27. Basic parameters in each car-following model

Vehicle Type	Control Mode	Acceleration (m/s ²)	Deceleration (m/s ²)	Desired headway (s)	Speed Deviation	Reaction time (s)
HDV	IDM	3	6.5	1.9	0.2	0.7
CAV-HDV	ACC	3.5	7.5	1.1	0	0.1
CAV-CAV	CACC	3.5	7.5	0.6	0	0.1

retains the previous control mode to provide hysteresis in the control process and perform a smooth transfer between two modes [187, 337]. The formula of the gap-closing control mode is calculated by recalibrating the parameters of control gains in Equation (B.11), and this study utilizes $k_2 = 0.04 \text{ s}^{-2}$ and $k_3 = 0.8 \text{ s}^{-1}$ according to [337].

Collision avoidance mode: The collision avoidance mode aims to avoid imminent rear-end collisions, and it is activated when the gap to the preceding vehicle is smaller than 100 m, and the gap and speed deviations are less than 0 and 0.1 m/s, respectively [208]. If the gap is between 100 m and 120 m, the subject vehicle retains the previous control mode to provide hysteresis in the control process and performs a smooth transfer between the two modes [187, 337]. The collision avoidance control mode was also derived by calibrating the parameters of gap control gains in Equation (B.11), and this study sets $k_2 = 0.8 \text{ s}^{-2}$ and $k_3 = 0.23 \text{ s}^{-1}$ according to [208].

Cooperative Adaptive Cruise Control

The CACC system, which could collect information from V2V and/or V2I communications, is a functional extension of the ACC system. It is noted that, when a CAV is following a CAV, the car-following system is changed into CACC mode. The additional information collected could help CAVs with the CACC system follow their predecessors with higher accuracy, shorter response time, and shorter headway compared to ACC vehicles [284].

Cruising control mode: The speed controller for the CACC system is the same as that for the ACC system. The cruising control mode is triggered when the time gap with respect to the preceding vehicle is larger than 2 s, and the gain k_1 in Equation (B.10) is set as 0.4 s^{-1} according to (Xiao, Wang, and Van Arem 2017; Liu, Xiao, and Kan 2018).

Gap control mode: The gap control mode for the CACC system is activated when the gap and speed deviations are smaller than 0.2 m and 0.1 m/s, respectively [337]. Compared to the gap control mode of the ACC vehicle, the speed of the subject CACC vehicle at the next time step $k + 1$ is calculated by:

$$v_{i,k+1} = v_{i,k} + k_4 e_{i,k} + k_5 \dot{e}_{i,k} \quad (\text{B.13})$$

$$\dot{e}_{i,k} = v_{i-1,k} - v_{i,k} - t_d a_{i,k} \quad (\text{B.14})$$

where $\dot{e}_{i,k}$ is the first-order derivative of the gap deviation $e_{i,k}$. The values of the control gains k_4 and k_5 in Equation (B.13) are calibrated as 0.45 s^{-2} and 0.25 s^{-1} , respectively [337]. Gap-closing control mode The gap-closing control mode in CACC is activated when the time-gap is less than 1.5 S. If the time-gap is between 1.5 S and 2 S, the subject vehicle would retain the previous control mode as a transition process [187, 337]. The Gap-closing control function is also calculated by calibrating the optimal gains in Equation (B.13), and they are set as $k_4 = 0.01 \text{ s}^{-2}$ and $k_5 = 0.05 \text{ s}^{-1}$ according to [337]. Collision avoidance mode The collision avoidance mode helps the CACC vehicle to change the velocity more smoothly and carefully when the time-gap to the preceding vehicle is less than 1.5 s and the gap deviation is negative [208]. The collision avoidance controller is also derived by calibrating the parameters of the gap control gains in Equation (B.13), and this study sets $k_4 = 0.45 \text{ s}^{-2}$ and $k_5 = 0.05 \text{ s}^{-1}$ according to [208].

B.3.3.2 Basic Parameters for Specific Traffic Simulation Models

The default lane change model “LC2013” in SUMO is employed for all vehicles. Table 27 indicates the basic parameters of the car-following behaviors of the HDVs and CAVs. According to the HCM (2016), the base saturation flow rate for HDV is 1900 passenger cars per hour per lane. In this case, the desired headway for HDVs is set as 1.9 s. The recommended headways for CAVs are adopted according to [206, 208]. When a CAV is following a CAV, the desired headway is 0.6 s. When a CAV is following a HDV, the car-following behavior will be shifted into ACC mode and the desired headway is 1.1 s. To model heterogeneous driving behaviors of the human drivers, the maximum speed for the HDV follows a normal distribution $N(1, 0.2)$ with respect to the speed limits. Also, the reaction time for HDV is 0.7 s, while the reaction time for the CAV is always 0.1 s. Moreover, Table 28 shows other specific parameters for ACC/CACC-controlled CAVs which are set according to previous research and projects [187, 208, 255].

B.3.4 Scenarios for Intersections: As identified in Chapter 3, a hypothetical isolated four-way intersection is selected as a basic scenario. An initial pre-timed signal scheme will be calculated for this typical intersection. Meanwhile, this typical intersection will be tested with different traffic demands and MPRs of CAVs. Moreover, two

Table 28. Specific factors for traffic simulation models

Factors	Default	Description	Models
minGap	2.5	Minimum Gap when standing (m)	all models
maxDecel	9	The maximum deceleration ability of vehicles of this type in case of emergency (in m/s ²)	all models
delta	4	acceleration exponent	IDM
stepping	0.25	the internal step length (in s) when computing follow speed	IDM
speedControlGain	-0.4	The control gain determining the rate of speed deviation (Speed control mode)	ACC
gapClosingControlGainSpeed	0.8	The control gain determining the rate of speed deviation (Gap closing control mode)	ACC
gapClosingControlGainSpace	0.04	The control gain determining the rate of positioning deviation (Gap closing control mode)	ACC
gapControlGainSpeed	0.07	The control gain determining the rate of speed deviation (Gap control mode)	ACC
gapControlGainSpace	0.23	The control gain determining the rate of positioning deviation (Gap control mode)	ACC
collisionAvoidanceGainSpace	0.8	The control gain determining the rate of positioning deviation (Collision avoidance mode)	ACC
collisionAvoidanceGainSpeed	0.23	The control gain determining the rate of speed deviation (Collision avoidance mode)	ACC
speedControlGainCACC	-0.4	The control gain determining the rate of speed deviation (Speed control mode)	CACC
gapClosingControlGainGap	0.01	The control gain determining the rate of positioning deviation (Gap closing control mode)	CACC
gapClosingControlGainGapDot	1.6	The control gain determining the rate of the positioning deviation derivative (Gap closing control mode)	CACC
gapControlGainGap	0.45	The control gain determining the rate of positioning deviation (Gap control mode)	CACC
gapControlGainGapDot	0.25	The control gain determining the rate of the positioning deviation derivative (Gap control mode)	CACC
collisionAvoidanceGainGap	0.45	The control gain determining the rate of positioning deviation (Collision avoidance mode)	CACC
collisionAvoidanceGainGapDot	0.05	The control gain determining the rate of the positioning deviation derivative (Collision avoidance mode)	CACC

*Source: SUMO User Documentation. <https://sumo.dlr.de/docs>

Table 29. Assumed through vehicle equivalents in the East Boundary

Approach	Movement	Volume (Veh/h)	Equivalent	Volume (TVU/h)	Lane group volume (TVU/h)	# of lanes	Volume/lane (TVU/h/lane)
EB	L	0.15X	1.05	0.1575X	0.1575X	1	0.1575X
	T	X	1	X	1.198X	2	1.198X/2=0.599 X
	R	0.15X	1.32	0.198X			

types of real-world intersections in North Carolina, including one isolated intersection and two adjacent intersections, will also be tested to analyze the impacts of CAVs on the intersection system performance.

B.3.4.1 Scenarios for Typical Isolated Intersection

Pretimed signal schemes and capacity for the intersection

According to the methods introduced in the Empirical Method part, an initial signal scheme and the corresponding intersection capacity could be determined. The following basic settings for the hypothetical isolated intersection are made as follow:

1. The intersection has four approaches, and each approach (or inlet) has one lane for left-turn-only traffic, one lane for through-only traffic, and one lane for through and right-turn traffic.

2. The pre-timed signal scheme is implemented. The cycle length is 100 s.

3. The traffic demands for left-turn and right-turn movements are both set as 15

Step1. Develop a phase plan: For this intersection, a protected left-turn phase will be used for all left-turn movements. The four phases signal scheme is set as: North-South direct movements, North-South left-turn movements, East-West direct movements, and East-West left-turn movements.

Step 2. Convert volumes to through-vehicle equivalents (TVU): The saturation flow ratio is unknown for this hypothetical intersection. According to assumption 3, the hourly through traffic demand is assumed as X. Then the left- and right-turn traffic demands are both 0.15X. The equivalent movement factor for left- and right-turn traffic is 1.05 and 1.32. Table 29 shows the detailed through vehicle equivalents in the East Boundary approach.

Step 3. Determine critical lane volumes: According to the step 1, a typical four-phase scheme is given. The critical volumes for each phase are presented in Table 30. The maximum sum of critical lane volumes V_C is obtained as: $V_C = (0.1575 + 0.599) \times 2X = 1.513X$.

Step 4. Determine Yellow and All-Red Intervals and lost time: The default timing of yellow (change) and all red (clearance) intervals for each phase: $y_{EW} = 3s$, $ar_{EW} = 1s$. Because $l_1 = e = 2$, the lost time per phase is given as: $t_L = l_1 + (y + ar - e) = y + ar = Y = 4s$.

Step 5. Obtain the traffic demands: With the loss time and given phase schemes, the maximum sum of critical lane volumes V_C could be calculated as:

$$V_C = \frac{1}{h} \left[3,600 - N t_L \left(\frac{3,600}{C} \right) \right] = \frac{1}{1.9} \left[3,600 - 4 \times 4 \left(\frac{3,600}{100} \right) \right] = 1592 \cdot \text{veh/hr.9} \quad (\text{B.15})$$

Table 30. Critical lane volume in each phase

	RING1		RING2		Critical volumes
Phase A1	EB-T&R	0.599X	WB-T&R	0.599X	0.599X
Phase A2	EB-L	0.1575X	WB-L	0.1575X	0.1575X
Phase B1	SB-T&R	0.599X	NB-T&R	0.599X	0.599X
Phase B2	SB-L	0.1575X	NB-L	0.1575X	0.1575X

Table 31. Calculated through vehicle equivalents in the East Boundary

Approach	Movement	Volume (Veh/h)	Equivalent	Volume (TVU/h)	Lane group volume (TVU/h)	# of lanes	Volume/lane (TVU/h/ln)
EB	L	158	1.05	166	166	1	166
	T	1052	1	1052	1260	2	630
	R	158	1.32	208			

Hence, the traffic demand for direct movements X is: $X=1592/1.513=1052$.

The detailed traffic demand for each direction is shown in Table 31. The sum of traffic demand in each approach is given as:

$$\text{Sum of traffic demand} = (158 + 1052 + 158)4 = 5472 \text{ veh/hr.} \quad (\text{B.16})$$

Step 6. Allocate effective green time to each phase: Based on the through vehicle equivalents for each lane group, the total effective green time g_i and specific green time for each phase are given as:

$$g_i = G_i + Y_i - t_{Li} = 100 - 4 \times 4 = 84s \quad (\text{B.17})$$

$$G_{pA1} = G_{pB1} = (C - Nt_L)CV_i/V_C = 84 \times 630/1592 = 33s \quad (\text{B.18})$$

$$G_{pA2} = G_{pB2} = (C - Nt_L)CV_i/V_C = 84 \times 166/1592 = 9s \quad (\text{B.19})$$

Intersection capacity based on the empirical method The intersection capacity could be calculated by summing the capacity of all lane groups. To obtain the lane group capacity, the basic lane capacity is calculated. For the HDVs, the headway is set as 1.9 s. The basic Saturation flow rate per lane:

$$s_0 = 3600/1.9 = 1895 \text{ veh/hr/lane} \quad (\text{B.20})$$

This basic saturation flow rate is adjusted for different conditions. The adjustment factors for left-turn movements with the exclusive lane is $f_{LT}=0.95$. Meanwhile, the right-turn movements with the shared lane are given as

$$f_{RT} = 1.0 - (0.15)P_{RT} = 1 - 0.15 \times 0.15 = 0.9775. \quad (\text{B.21})$$

The exclusive left-turn lane capacity:

$$c_{left} = s_i g_i / C = 1895 \times 0.95 \times 9/100 = 1625 \text{ pcu/hr} \quad (\text{B.22})$$

The direct traffic-only lane capacity:

$$c_{direct} = s_i g_i / C = 1895 \times 33/100 = 625 \text{ pcu/hr} \quad (\text{B.23})$$

The direct and right traffic (i.e., shared right) lane capacity:

$$c_{sharedRight} = s_i g_i / C = 1895 \times 0.9775 \times 33/100 = 611 \text{ pcu/hr} \quad (\text{B.24})$$

The total capacity of the intersection is given by summing all lane groups in 4 approaches:

$$\text{Capacity} = 4 \times (162 + 625 + 611) = 4 \times 1398 = 5592 \text{ pcu/hr} \quad (\text{B.25})$$

Table 32. Traffic volume of each traffic movement at the isolated intersection

Roadway	N. Tryon St.			N. Tryon St.			Harris Blvd.			Harris Blvd.		
Direction	Southbound			Northbound			Westbound			Eastbound		
	R	T	L	R	T	L	R	T	L	R	T	L
Volume	216	293	353	251	397	404	239	1229	257	169	1050	168

The capacity calculated by the empirical method is nearly the sum of saturated traffic demands (5,472 pcu/hr) calculated in the previous section. This value would be compared with the capacity (i.e., maximum through) obtained by the simulation methods.

Scenarios for Typical Isolated Intersection

All simulation scenarios are processed in the Simulation of Urban MObility (SUMO) by the TraCI-Python interface. Each training episode of the simulation is 3600-s with a 0.1-s time step. A ten-minute (600 s) warm-up period is added at the beginning of each simulation. This warm-up period aims to eliminate the impacts of insufficiency of traffic generation at the first ten minutes of the simulation. The pre-timed signal scheme has a 100-s cycle length and the phases are set as North-South direct movements (33 s), North-South left-turn movements (9 s), East-West direct movements (33 s), East-West left-turn movements (9 s). The yellow and all-red time is 4 s per phase.

In the microscopic simulation scenarios, saturated traffic throughput (or maximum throughput) is utilized to estimate the capacity of the intersection. The traffic generation obeys the uniform distribution to maintain the peak-hour traffic demands all the time. The maximum throughput is obtained by increasing the traffic demands of the intersection and obtaining a stable throughput value. Then, traffic demands with different MPRs of CAVs are also tested to obtain the maximum throughput. The detailed simulation scenarios are given as follows.

1). For scenarios with only HDVs, by increasing the traffic demands from 500 to 8000 veh/hr, each simulation would get the throughputs with different traffic demands and the traffic performance in the scenario with maximum throughput.

2). For scenarios with the CAVs, the MPRs of CAVs would increase from 0 to 100% with 10% per step. Then, each simulation would obtain the throughputs with different traffic demands and the traffic performance in the scenario with maximum throughput.

B.3.4.2 Scenarios for Intersections in North Carolina

One isolated intersection in Charlotte, NC

For the selected isolated intersection in Charlotte, NC, the speed limit of this study site is 45 miles/hour. The midday peak-hour traffic volume, from 12:30 p.m. to 1:30 p.m., on April 3rd, 2018 was collected from the City of Charlotte according to Liu and Fan [189]. Table 32 presents the detailed traffic volume of each traffic movement during the study period. The selected isolated intersection uses a pre-timed signal control scheme with a 140s cycle length. The detailed time splits and phases for the pre-timed scheme are shown in Figure 59. The simulation scenarios would be conducted under 100% HDVs and 100% CAVs scenarios. The impacts of CAVs on traffic performance would be analyzed.

Two adjacent intersections in Greensboro, NC

For the selected two adjacent intersections in Greensboro, the speed limit of this study site is 35 miles/hour. The afternoon peak-hour traffic volume, from 4:45 p.m. to 5:45 p.m., on February 7th, 2018 was collected from the Greensboro Department of Transportation. Figure 60 and Figure 61 present the detailed traffic volume of each traffic movement at two adjacent intersections. Both of the two adjacent intersections are controlled by pre-timed signal control schemes with a 90 s cycle length. The offset time between two adjacent intersections is 75s. The detailed time split and phases for the pre-timed schemes are shown in Figure 62. The simulation scenarios would be conducted under 100% HDVs and 100% CAVs scenarios. The impacts of CAVs on traffic performance would be analyzed.

B.3.5 Summary

In this chapter, empirical methods for intersection capacity calculation and micro-simulation methods for HDVs and CAVs are introduced. After that, an initial pre-timed signal scheme is designed for a hypothetical isolated four-way intersection. Also, the intersection capacity is calculated by the empirical method and would be used to compare with the capacity obtained by the micro-simulation method. Specific scenarios for this typical intersection are designed considering different traffic demands and MPRs of CAVs. Moreover, two types of real-world intersections in North Carolina, including one isolated intersection and two adjacent intersections, will also be tested to investigate the potential impacts of CAV technologies on the intersection system. These are basic preparations for simulating



Figure 59. Pre-timed signal scheme for the isolated intersection intersection capacity with CAVs in the next tasks.

B.4 USING SIMULATIONS TO EXAMINE THE ESTABLISHED MODELING FRAMEWORK

B.4.1 Introduction

As discussed in the potential intersections selected in Chapter B.3, this chapter presents the numerical results of the simulation for the designed scenarios for each intersection. The following parts are mainly organized into two sections. In Section B.4.2, a hypothetical isolated four-way intersection is utilized to set up a basic scenario for the lane-level and intersection-level capacity analysis. The intersection capacity is first analyzed by calculating adjustment factors for saturation headway and saturation traffic flow rate for each lane group under different MPRs of CAVs. Then, the fitted curves and functions for the maximum throughput and other traffic performance indicators of the whole intersection under different MPRs of CAVs are calibrated and investigated. In Section B.4.3, three intersection scenarios, including one hypothetical isolated intersection, one isolated intersection in Charlotte, and two-adjacent intersections in Greensboro, are employed to investigate the impacts of CAV penetration rates on the intersection with fixed traffic demands. Finally, section B.4.4 concludes this chapter with a summary.

B.4.2 Capacity Analysis for Typical Isolated Intersection

B.4.2.1 Intersection Capacity Analysis at the Lane Level

As defined in HCM (2016), saturation headway is the average headway between the fifth and fifteen vehicles in a standing queue when the intersection signal light changes from red to green. The first four headways are not included due to the impacts of start-up loss time. The headway is calculated by the time gap when two successive vehicles (front bumper) are passing over the stop line. In this research, the base saturation headway rate s_0 is obtained by dividing 3600 s by the saturation headway of the human-driven vehicles h_{HDV} . Considering the impacts of CAVs, the saturation flow rate s^* could be adjusted by the headway adjustment factor f_h , according to equation (B.26) or the saturation flow rate (SFR) adjustment factor f_s , according to equation (B.28).

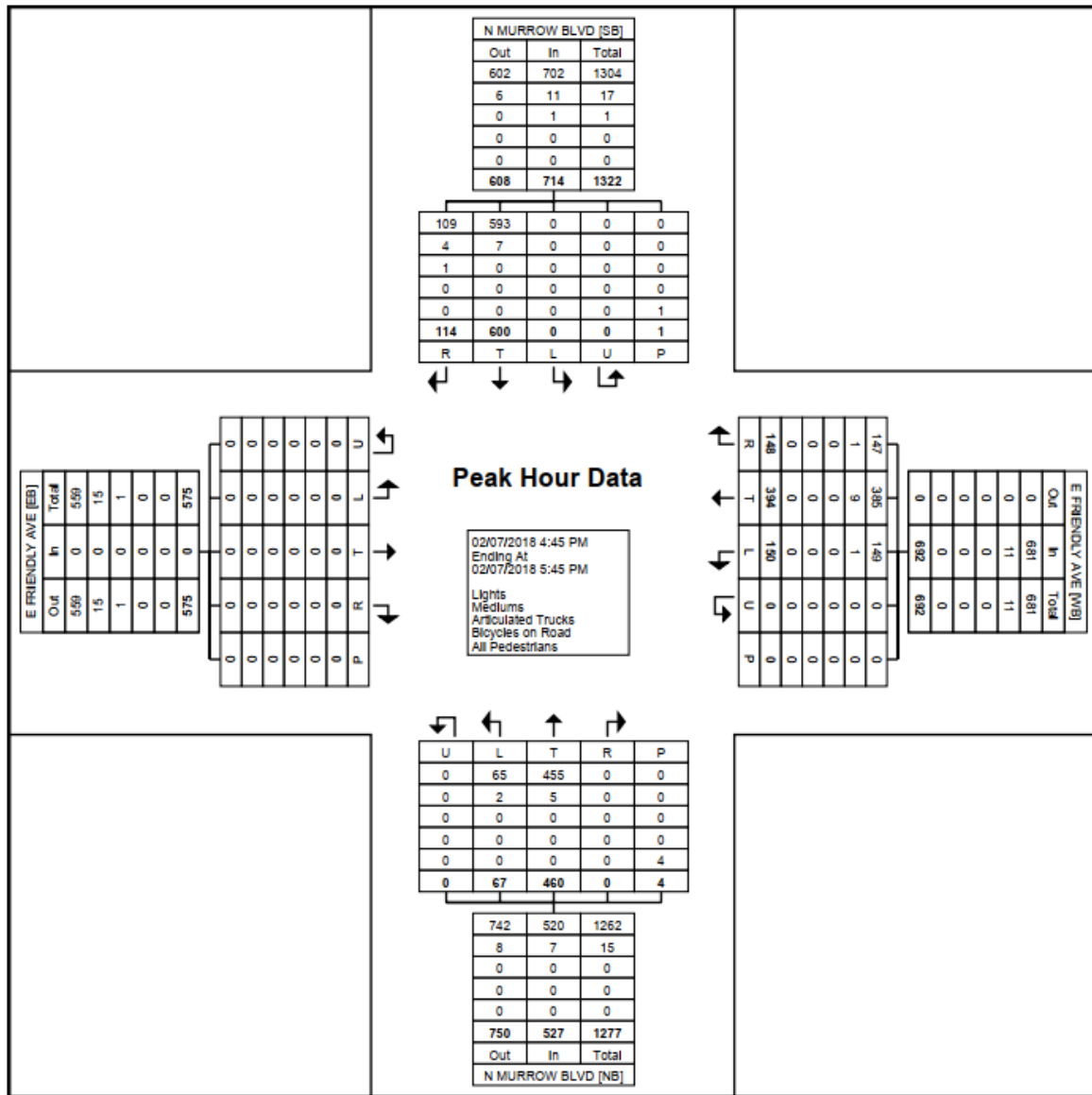
$$f_{h(CAV \text{ rate} = \alpha)} = \frac{\text{headway}_{CAV \text{ rate} = \alpha}}{\text{headway}_{HDV}} \quad (B.26)$$

$$S^* = \frac{3600}{f_h \times h_{HDV}} \quad (B.27)$$

$$f_{S(CAV \text{ rate} = \alpha)} = \frac{1}{f_{h(CAV \text{ rate} = \alpha)}} \quad (B.28)$$

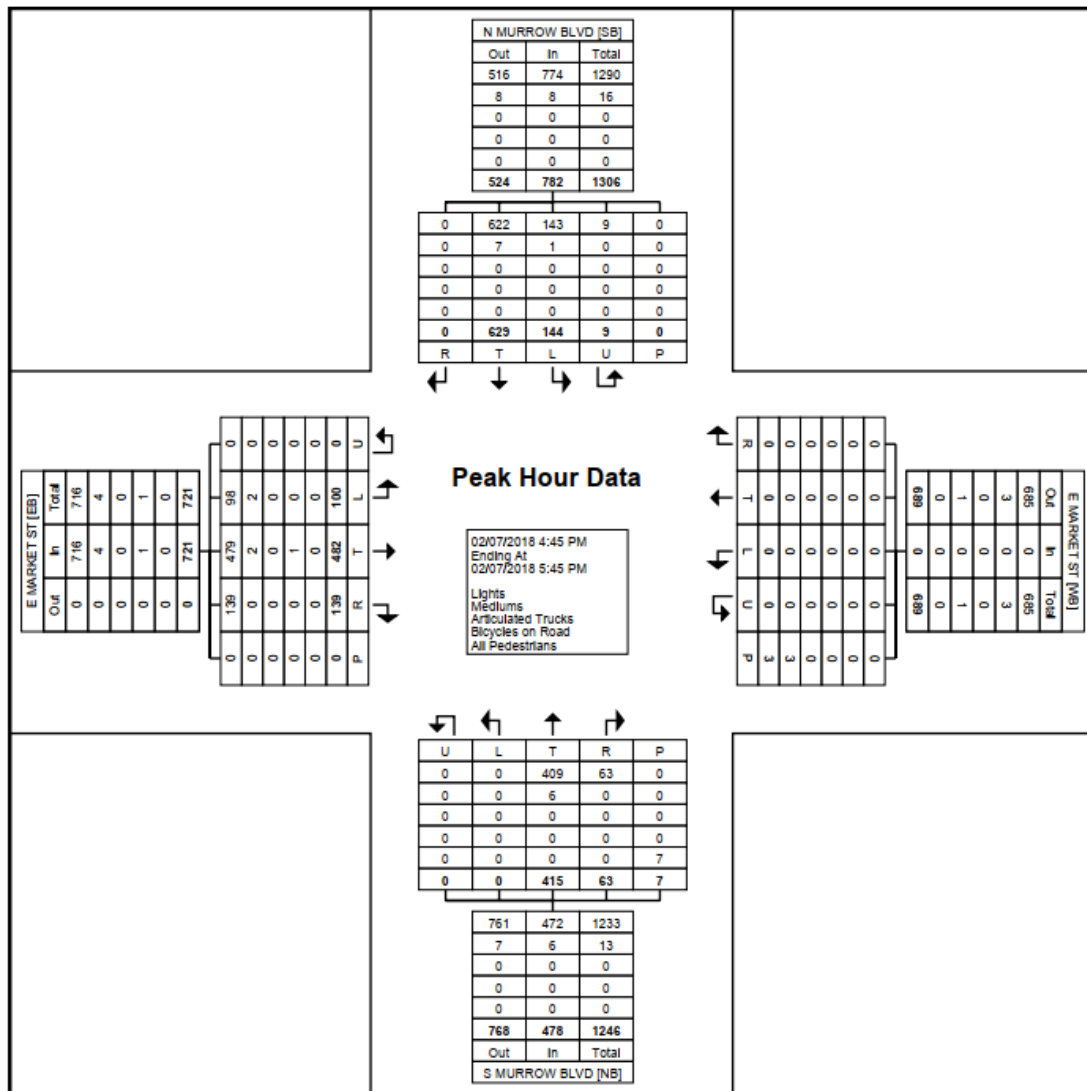
$$S^* = f_s \times s_0 = f_s \frac{3600}{h_{HDV}} \quad (B.29)$$

With the increase of the traffic demand for each lane, the lane level throughput reaches a maximum



Turning Movement Peak Hour Data Plot (4:45 PM)

Figure 60. Traffic volume of each movement at the first intersection (Friendly Ave. & Murrow Blvd.)



Turning Movement Peak Hour Data Plot (4:45 PM)

Figure 61. Traffic volume of each movement at the second intersection (Market St. & Murrow Blvd.)



(a) Pre-timed signal scheme of the first intersection (Friendly Ave. & Murrow Blvd.)



(b) Pre-timed signal scheme of the second intersection (Market St. & Murrow Blvd.)

Figure 62. Pre-timed signal schemes for two adjacent intersections

Table 33. Saturation headway for each lane under different MPRs of CAVs

	Headway (s)		
CAV rate	Exclusive through	Exclusive Left	Shared right
0	2.117	2.298	2.317
0.1	2.083	2.252	2.24
0.2	2.029	2.203	2.263
0.3	1.871	1.996	2.174
0.4	1.742	1.957	2.045
0.5	1.738	1.945	1.934
0.6	1.566	1.718	1.888
0.7	1.367	1.604	1.722
0.8	1.311	1.369	1.604
0.9	1.068	1.26	1.518
1	0.934	1.174	1.335

value, which represents the saturated traffic demand. In this study, lanes in each approach of the hypothetical four-way intersection include one exclusive through traffic lane, one exclusive left-turn traffic lane, and one shared-right-and-through traffic lane. In each simulation, the first 600s of the 3600s simulation is set as the warm-up time. The traffic is generated with a uniform distribution. The average values of all headways for the fifth to the fifteenth vehicle crossing the stop line when the light changed from red to yellow are obtained. Table 33 presents the saturation headway for each lane of the isolated intersection under saturated traffic demand scenarios. With the increase of MPRs of CAVs, the saturation headways for each lane also present different degrees of reduction. In the simulation, the desired time gap value for HDVs, ACC-mode-controlled CAVs, and CACC-mode-controlled CAVs is 1.9 s, 1.1 s, and 0.6 s, respectively. It is noted that the time gap is only part of the headway, which also includes the travel time used for the length of the front vehicle. The saturation headway for the exclusive through traffic lane is 2.117 for only-HDV conditions. Also, the saturation headways for the exclusive left-turn and shared-right lanes are slightly larger than the exclusive through lane due to the impacts of turning vehicles. With 100% CAVs, the saturation headways for the exclusive through traffic lane, exclusive left-turn traffic lane, and shared-right-and-through traffic lane decrease by 55.8%, 48.9%, and 42.4%, respectively.

According to the saturation headway results shown in Table 33, the adjustment factors for the saturation headway and saturation flow rate under different MPRs of CAVs are summarized in Table 34. The adjustment factors are used to modify the condition with only HDVs. Under 100% MPRs of CAVs, the saturation headways of through-only, left-turn-only, and shared-right-and-through traffic lanes are about 0.441, 0.511, and 0.576, respectively, with regard to the condition of only HDVs. Meanwhile, with 100% MPRs of CAVs, the saturation flow rates for the through-only, left-turn-only, and shared-right-and-through traffic lanes could increase about 126.8%, 95.7%, and 73.6%, respectively, compared to the only HDVs condition.

Figure 63 and Figure 64 also indicate the tendency of the saturation headway and saturation flow rate adjustment factors under different MPRs of CAVs. Contrary tendency results are observed in saturation flow rate adjustment factors as they are reciprocal (or inverse) of the saturation headway adjustment factors. It is noted that the saturation headway adjustment factors for the exclusive through lane are smaller than the exclusive left-turn lane after 40% MPRs of CAVs. Also, saturation headway adjustment factors of the exclusive through lane and exclusive left-turn lane are always smaller than the shared-right-and-through traffic lane. The exclusive through traffic lane shows the largest deduction as it is not affected by the turning vehicles. The shared-right-and-through traffic lane has

Table 34. Adjustment factors for saturation headway and saturation flow rate for each lane group under different MPRs of CAVs

CAV rate	Saturation headway adjustment factors			Saturation flow rate adjustment factors		
	Exclusive through	Exclusive left	Shared right	Exclusive through	Exclusive left	Shared right
0.1	0.984	0.98	0.967	1.016	1.02	1.034
0.2	0.958	0.959	0.977	1.044	1.043	1.024
0.3	0.884	0.869	0.938	1.131	1.151	1.066
0.4	0.823	0.852	0.883	1.215	1.174	1.133
0.5	0.821	0.847	0.835	1.218	1.181	1.198
0.6	0.74	0.748	0.815	1.351	1.337	1.227
0.7	0.645	0.698	0.743	1.55	1.433	1.346
0.8	0.632	0.638	0.716	1.582	1.567	1.397
0.9	0.505	0.548	0.655	1.98	1.825	1.527
1	0.441	0.511	0.576	2.268	1.957	1.736

the minimum deduction in the headway as it both includes turning and straight vehicles. The heterogeneous traffic movements (mixed turning and straight movements) could have negative impacts on the deduction of headways.

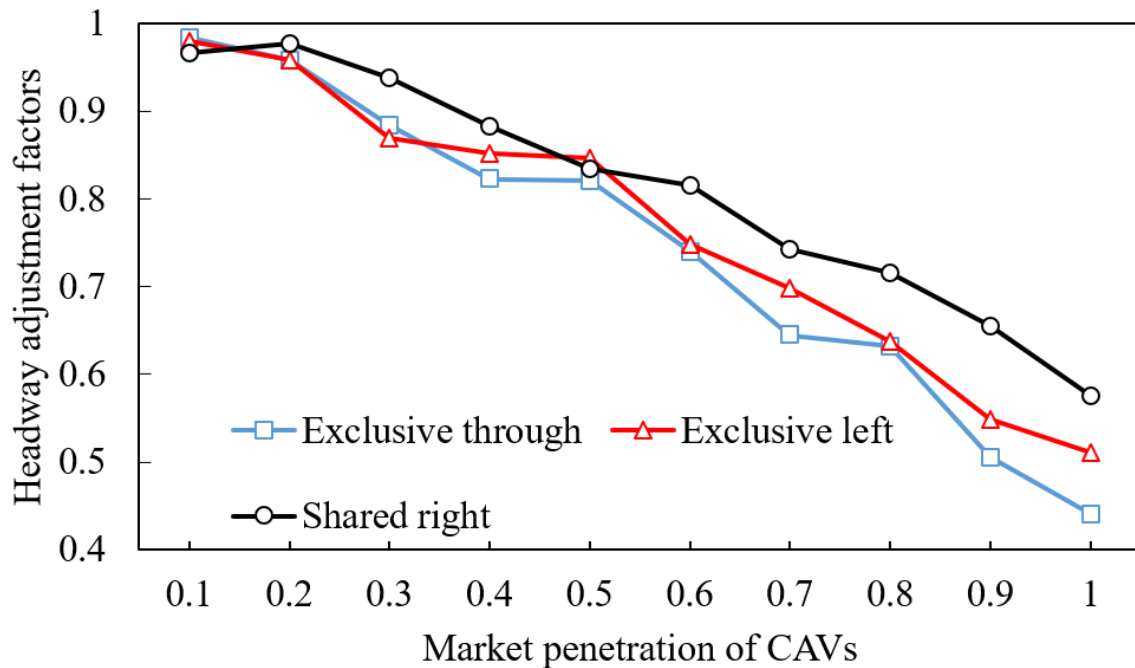


Figure 63. Headway adjustment factors under different MPRs of CAVs

B.4.2.2 Intersection Capacity Analysis at the Intersection Level

Intersection Capacity with only Human Driving Vehicles

In the simulation, the maximum throughput of the isolated intersection is obtained with the increase in traffic demands. The capacity (simulated maximum throughput) of the isolated intersection is obtained under different MPRs of CAVs conditions. After that, the traffic performances are investigated under maximum throughput scenarios. The fitted curves and adjustment factors for the intersection capacity under different MPRs of CAVs are analyzed.

At first, all simulated vehicles are set as human-driving vehicles. During the simulation, the traffic demand for the whole intersection increases from 500 to 8000 veh/hr. As shown in Figure 65, the throughput reaches a maximum value of 4938 veh/hr with the increase of traffic demands. The specific traffic performance, including total waiting time, total CO₂ emission, and total fuel consumption are given in Table 35. This maximum throughput value for the only-HDV condition is set as a basic value for scenarios with different MPRs of CAVs.

Intersection Capacity under Mixed Traffic Conditions

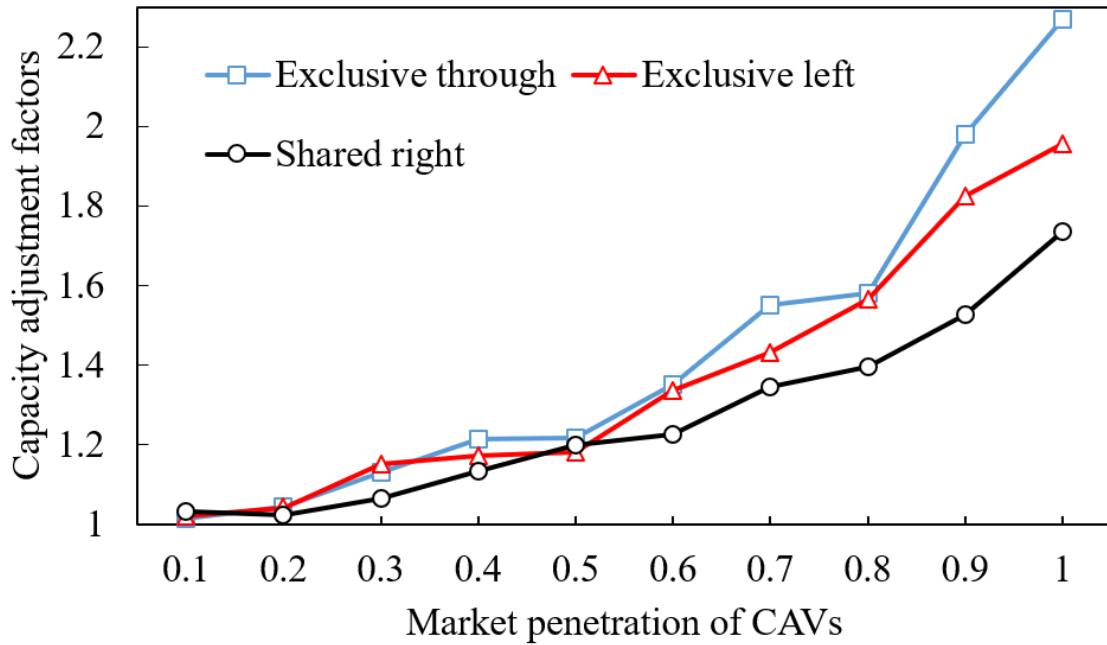


Figure 64. Saturation flow rate adjustment factors under different MPRs of CAVs

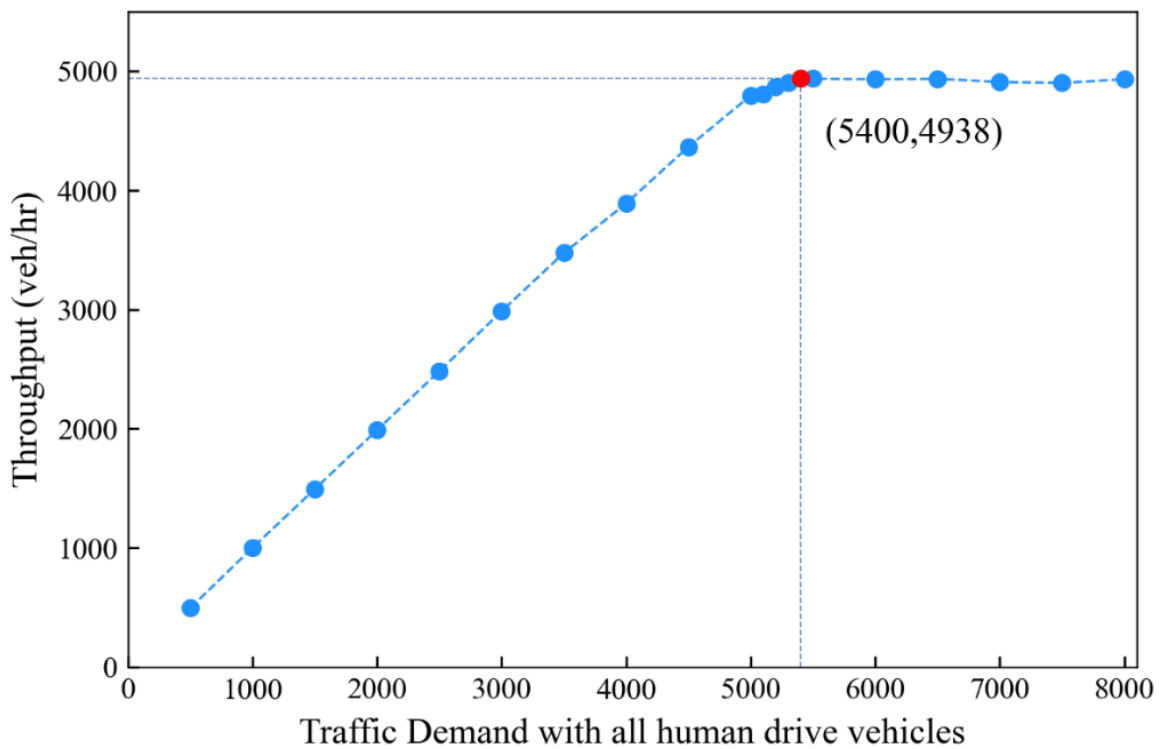


Figure 65. Traffic throughput with all human drive vehicles

Table 35. Intersection system performance under different traffic demands

Traffic demand	Total waiting time (s)	Avg. waiting time (s)	Total CO2 (kg)	Avg. CO2 (kg)	Total Fuel (L)	Avg. Fuel (L)	Throughput
500	11870.2	23.74	106.405	0.213	45.74	0.091	494
1000	22941.1	22.94	209.97	0.21	90.259	0.09	1000
1500	32283.5	21.52	303.919	0.203	130.645	0.087	1492
2000	43315	21.66	405.772	0.203	174.428	0.087	1988
2500	55362.3	22.14	507.702	0.203	218.244	0.087	2482
3000	67961.8	22.65	611.889	0.204	263.03	0.088	2985
3500	103633.2	29.61	765.899	0.219	329.235	0.094	3474
4000	188678.1	47.17	1010.768	0.253	434.498	0.109	3889
4500	298865.9	66.41	1300.891	0.289	559.216	0.124	4365
5000	456866	91.37	1683.653	0.337	723.758	0.145	4795
5100	526753.9	103.29	1819.08	0.357	781.976	0.153	4806
5200	573650.6	110.32	1935.533	0.372	832.037	0.16	4869
5300	611847.6	115.44	2056.597	0.388	884.081	0.167	4906
5400	658796.4	122	2180.461	0.404	937.329	0.174	4938
5500	690104.4	125.47	2424.438	0.441	1042.212	0.189	4937
6000	847410.6	141.24	3095.41	0.516	1330.657	0.222	4932
6500	951538.2	146.39	3434.703	0.528	1476.517	0.227	4936
7000	1000533	142.93	3592.943	0.513	1544.543	0.221	4908
7500	1038971	138.53	3682.411	0.491	1583.005	0.211	4901
8000	998487.1	124.81	3716.553	0.465	1597.683	0.2	4931

Additionally, scenarios with different MPRs of CAVs are simulated with different traffic demands. When a CAV is following a HDV, the car-following system is changed into the ACC mode. When a CAV is following a CAV, the car-following system is switched into the CACC mode for a closer car-following behavior. As shown in Figure 66 to Figure 75, the maximum throughputs (points marked with red color) of the whole intersection are obtained with the increase of traffic demands under different MPRs of CAVs (increase from 10% to 100% with 10% per step). The specific traffic performances (including the total waiting time, total CO2 emission, and total fuel consumption) under different traffic demands are also given in Table 36 to Table 45. With the increase of MPRs of CAVs, the maximum throughput of the intersection also increases accordingly. With 100% MPRs of CAVs, the maximum throughput reaches 8413 veh/hour.

Performance Per Simulation Step under Maximum Throughput

The detailed traffic performance per simulation step is also documented when the maximum throughput is reached. The simulation time is 4200 s and the first 600 s is the warm-up time. Also, the simulation step is set as 0.1 s to update the speed and driving decisions because the CAV simulation requires a reaction time that is less than 1 s. Figures 76 to 78 show the waiting time, CO2 emission, and fuel consumption per simulation step, respectively. These curves show periodic fluctuations with the periodic changes of the signal phase. When the traffic light changes to green, the queuing vehicles pass through the intersection and decrease the waiting time. Figure 79 presents the cumulative throughput within 3600 s. This throughput is steadily increasing since the traffic flow is saturated for this intersection.

Summary of Intersection-level Results

Figure 80 presents the throughput under different MPRs of CAVs. All traffic performances under saturated traffic flow with different MPRs of CAVs are summarized in Table 46. The maximum throughput increases with the increase of CAV penetration rates. Also, the change rates of the maximum throughput are summarized in the last column of Table 46. It is noted that, with 100% MPRs of CAVs, the maximum throughput of this isolated intersection could increase about 70.4% compared to the scenario with no CAVs.

With the maximum throughput (veh/hour) being summarized in Table 46, this research obtains the fitting curve of the maximum throughput (y) with regard to the MPRs of CAVs (x). The fitting curve is presented in Figure 81 and the fitting formula is shown in equation ((B.30). The maximum throughput increases steadily under 60% MPRs of CAVs and increases rapidly after 70% MPRs of CAVs.

$$MaximumThroughput = 2969MPR^3 - 1010MPR^2 + 1505MPR + 4914 \quad (B.30)$$

With the total CO2 emission (kg), total fuel consumption (L), and total waiting time (10^6 s) of the saturated traffic flow summarized in Table 46, the fitting formulas of the CO2 emission, fuel consumption, and waiting time with regard to the MPRs of CAVs are indicated in equation B.31 to equation B.33. Meanwhile, the fitting curves of these three indicators are presented in Figure 82 to Figure 84. The maximum throughput increases steadily under 60%

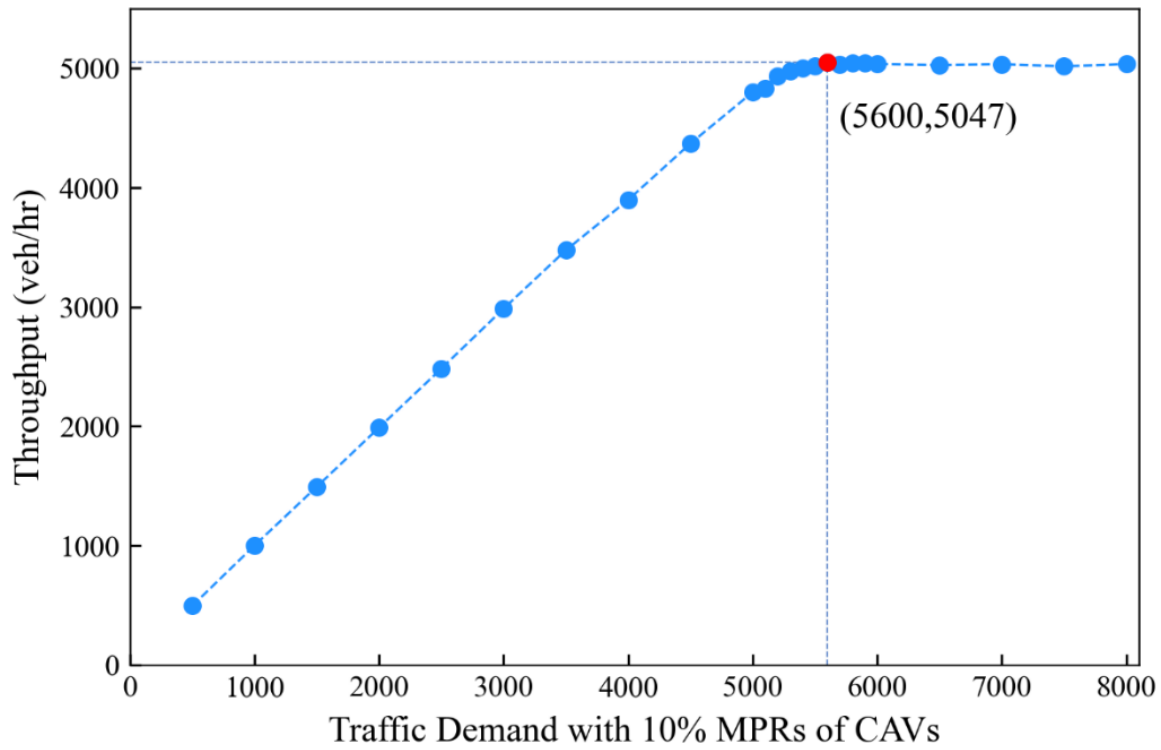


Figure 66. Traffic throughput under 10% MPRs of CAVs

Table 36. Intersection system performance under 10% MPRs of CAVs

Traffic demand	Total waiting time (s)	Average waiting time (s)	Total CO2 (kg)	Avg. CO2 (kg)	Total Fuel (L)	Avg. Fuel (L)	Throughput
500	11897	23.79	106.406	0.213	45.74	0.091	494
1000	23113.9	23.11	210.895	0.211	90.66	0.091	1000
1500	32513.7	21.68	305.141	0.203	131.17	0.087	1492
2000	43181	21.59	406.596	0.203	174.78	0.087	1988
2500	55729.8	22.29	510.779	0.204	219.57	0.088	2482
3000	67575.5	22.53	613.168	0.204	263.58	0.088	2985
3500	104163.2	29.76	770.182	0.22	331.08	0.095	3475
4000	185124	46.28	1007.809	0.252	433.23	0.108	3896
4500	285254.2	63.39	1277.767	0.284	549.28	0.122	4369
5000	416404.2	83.28	1617.937	0.324	695.51	0.139	4799
5100	497837	97.62	1779.868	0.349	765.12	0.15	4829
5200	522937.4	100.56	1842.598	0.354	792.09	0.152	4935
5300	569849.9	107.52	1960.683	0.37	842.85	0.159	4979
5400	649277.8	120.24	2138.134	0.396	919.13	0.17	4998
5500	656012.6	119.28	2252.936	0.41	968.48	0.176	5016
5600	697819	124.61	2385.617	0.426	1025.52	0.183	5047
5700	724951.6	127.18	2598.42	0.456	1117	0.196	5033
5800	815327.9	140.57	2837.354	0.489	1219.72	0.21	5042
5900	829402.8	140.58	2925.053	0.496	1257.42	0.213	5044
6000	861395.1	143.57	3077.237	0.513	1322.84	0.22	5035
6500	973131.1	149.71	3462.993	0.533	1488.68	0.229	5027
7000	1001880	143.13	3620.392	0.517	1556.34	0.222	5034
7500	1035871	138.12	3683.266	0.491	1583.37	0.211	5016
8000	1031780	128.97	3721.681	0.465	1599.89	0.2	5035

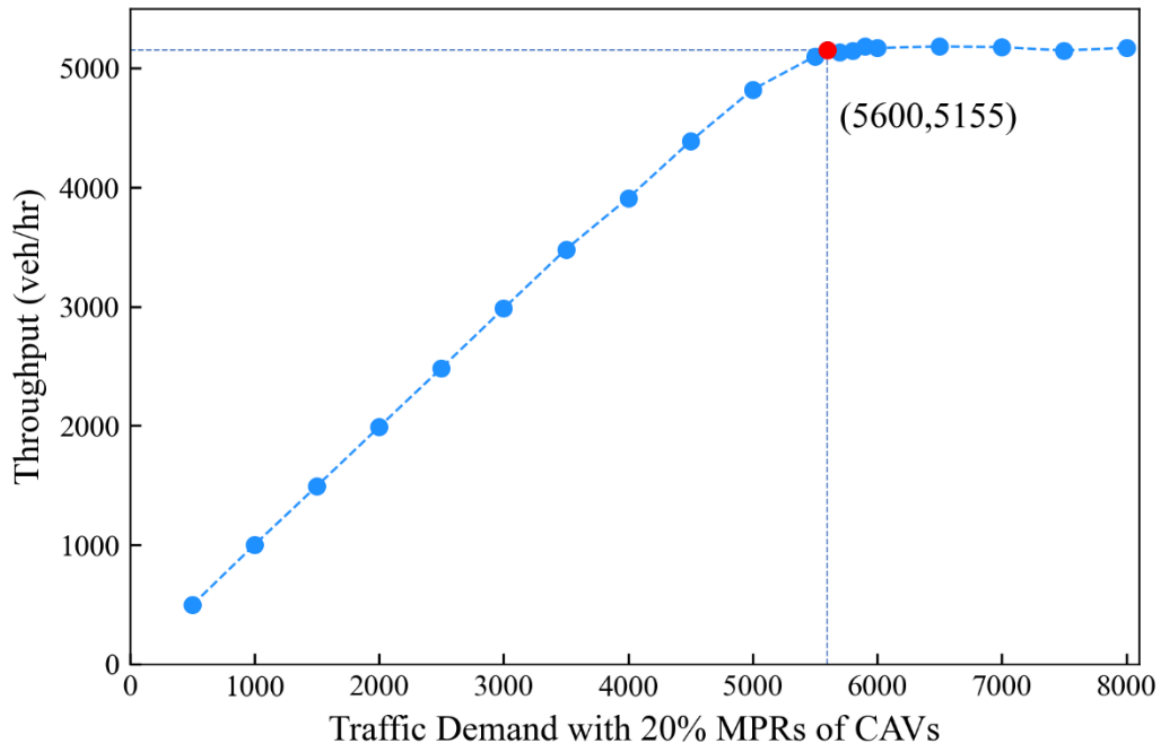


Figure 67. Traffic throughput under 20% MPRs of CAVs

Table 37. Intersection system performance under 20% MPRs of CAVs

Traffic demand	Total waiting time (s)	Average waiting time (s)	Total CO2 (kg)	Avg. CO2 (kg)	Total Fuel (L)	Avg. Fuel (L)	Throughput
500	12009.5	24.02	106.715	0.213	45.873	0.092	494
1000	23230.6	23.23	211.503	0.212	90.918	0.091	1000
1500	32624.9	21.75	306	0.204	131.539	0.088	1492
2000	43292.1	21.65	408	0.204	175.385	0.088	1988
2500	56185.8	22.47	513.269	0.205	220.637	0.088	2482
3000	67242.4	22.41	614.46	0.205	264.135	0.088	2983
3500	97471.8	27.85	758.288	0.217	325.963	0.093	3479
4000	169506.5	42.38	984.273	0.246	423.108	0.106	3909
4500	259312.2	57.62	1238.702	0.275	532.482	0.118	4386
5000	387094.9	77.42	1573.665	0.315	676.475	0.135	4820
5500	630842.4	114.7	2153.008	0.391	925.526	0.168	5099
5600	695985.4	124.28	2282.991	0.408	981.403	0.175	5155
5700	706945.4	124.03	2431.9	0.427	1045.419	0.183	5133
5800	768938.1	132.58	2701.448	0.466	1161.294	0.2	5149
5900	815897.8	138.29	2767.774	0.469	1189.807	0.202	5183
6000	855111.2	142.52	2917.315	0.486	1254.094	0.209	5168
6500	959093.1	147.55	3421.156	0.526	1470.691	0.226	5182
7000	1020936	145.85	3615.142	0.516	1554.085	0.222	5176
7500	1071136	142.82	3677.893	0.49	1581.061	0.211	5148
8000	1051282	131.41	3760.009	0.47	1616.362	0.202	5171

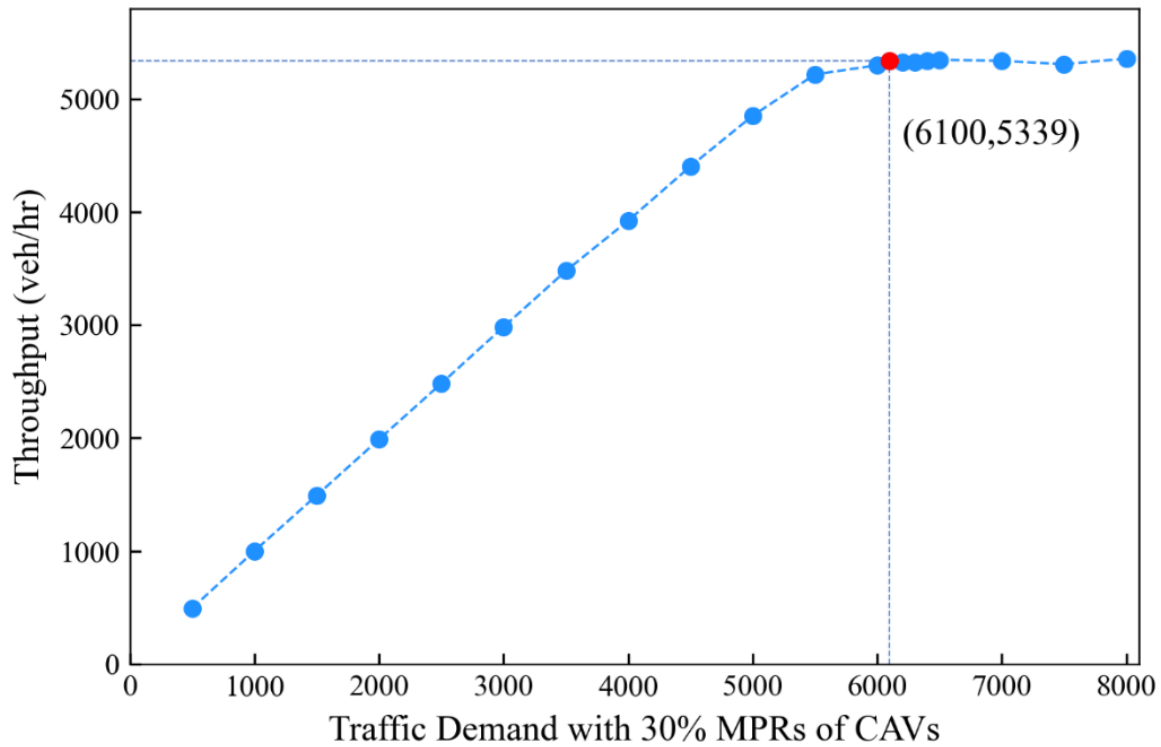


Figure 68. Traffic throughput under 30% MPRs of CAVs

Table 38. Intersection system performance under 30% MPRs of CAVs

Traffic demand	Total waiting time (s)	Average waiting time (s)	Total CO2 (kg)	Avg. CO2 (kg)	Total Fuel (L)	Avg. Fuel (L)	Throughput
500	12078.3	24.16	107.094	0.214	46.036	0.092	494
1000	23374.2	23.37	212.269	0.212	91.247	0.091	1000
1500	32929.7	21.95	307.566	0.205	132.212	0.088	1492
2000	43700.7	21.85	409.803	0.205	176.161	0.088	1988
2500	56247	22.5	516.019	0.206	221.819	0.089	2482
3000	67615.7	22.54	617.735	0.206	265.543	0.089	2983
3500	93007.9	26.57	752.304	0.215	323.39	0.092	3478
4000	149575.9	37.39	949.79	0.237	408.285	0.102	3923
4500	235797.3	52.4	1203.821	0.268	517.487	0.115	4403
5000	320516.5	64.1	1455.911	0.291	625.855	0.125	4851
5500	526064.5	95.65	1915.574	0.348	823.455	0.15	5217
6000	779754.6	129.96	2772.06	0.462	1191.648	0.199	5298
6100	860257.7	141.03	2922.059	0.479	1256.132	0.206	5339
6200	901555.2	145.41	3087.21	0.498	1327.129	0.214	5323
6300	932138.9	147.96	3148.772	0.5	1353.594	0.215	5325
6400	947449.8	148.04	3230.325	0.505	1388.652	0.217	5336
6500	975596.3	150.09	3383.753	0.521	1454.611	0.224	5347
7000	1077718	153.96	3625.048	0.518	1558.341	0.223	5337
7500	1093178	145.76	3727.835	0.497	1602.529	0.214	5307
8000	1104663	138.08	3809.146	0.476	1637.484	0.205	5358

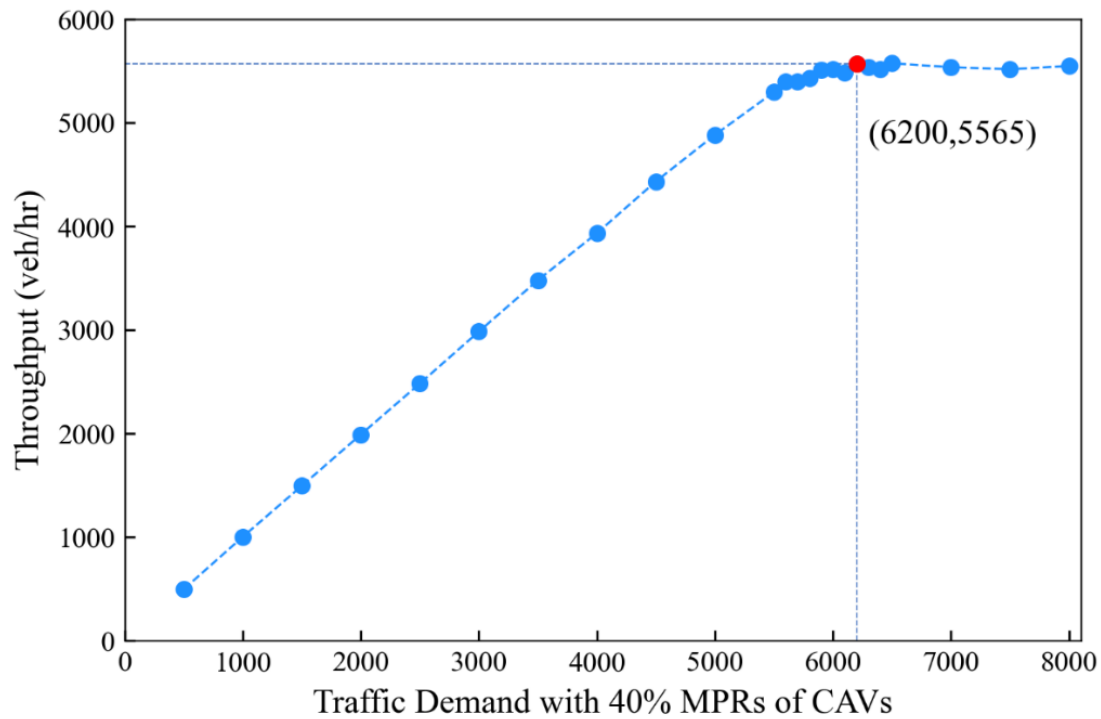


Figure 69. Traffic throughput under 40% MPRs of CAVs

Table 39. Intersection system performance under 40% MPRs of CAVs

Traffic demand	Total waiting time (s)	Average waiting time (s)	Total CO2 (kg)	Avg. CO2 (kg)	Total Fuel (L)	Avg. Fuel (L)	Throughput
500	12073.6	24.15	107.113	0.214	46.044	0.092	494
1000	23538.7	23.54	213.295	0.213	91.689	0.092	1000
1500	33212.2	22.14	309.762	0.207	133.156	0.089	1492
2000	44222	22.11	413.538	0.207	177.766	0.089	1988
2500	56715.1	22.69	518.916	0.208	223.064	0.089	2480
3000	68198.5	22.73	622.378	0.207	267.539	0.089	2982
3500	92387.2	26.4	755.034	0.216	324.564	0.093	3478
4000	136609.2	34.15	932.025	0.233	400.648	0.1	3932
4500	195053.3	43.35	1132.02	0.252	486.621	0.108	4432
5000	285716.2	57.14	1392.478	0.278	598.586	0.12	4881
5500	460509.9	83.73	1805.95	0.328	776.329	0.141	5294
5600	475953.7	84.99	1866.587	0.333	802.396	0.143	5399
5700	582916.8	102.27	2079.087	0.365	893.746	0.157	5393
5800	626975.9	108.1	2191.562	0.378	942.098	0.162	5429
5900	688060	116.62	2324.788	0.394	999.369	0.169	5505
6000	749110.2	124.85	2476.202	0.413	1064.461	0.177	5512
6100	818003.7	134.1	2765.329	0.453	1188.753	0.195	5480
6200	848790.4	136.9	2854.666	0.46	1227.158	0.198	5565
6300	876141.9	139.07	2991.073	0.475	1285.799	0.204	5537
6400	952157	148.77	3137.95	0.49	1348.939	0.211	5515
6500	953262.5	146.66	3276.031	0.504	1408.3	0.217	5572
7000	1114911	159.27	3613.613	0.516	1553.424	0.222	5535
7500	1161375	154.85	3785.574	0.505	1627.349	0.217	5515
8000	1145895	143.24	3864.965	0.483	1661.479	0.208	5546

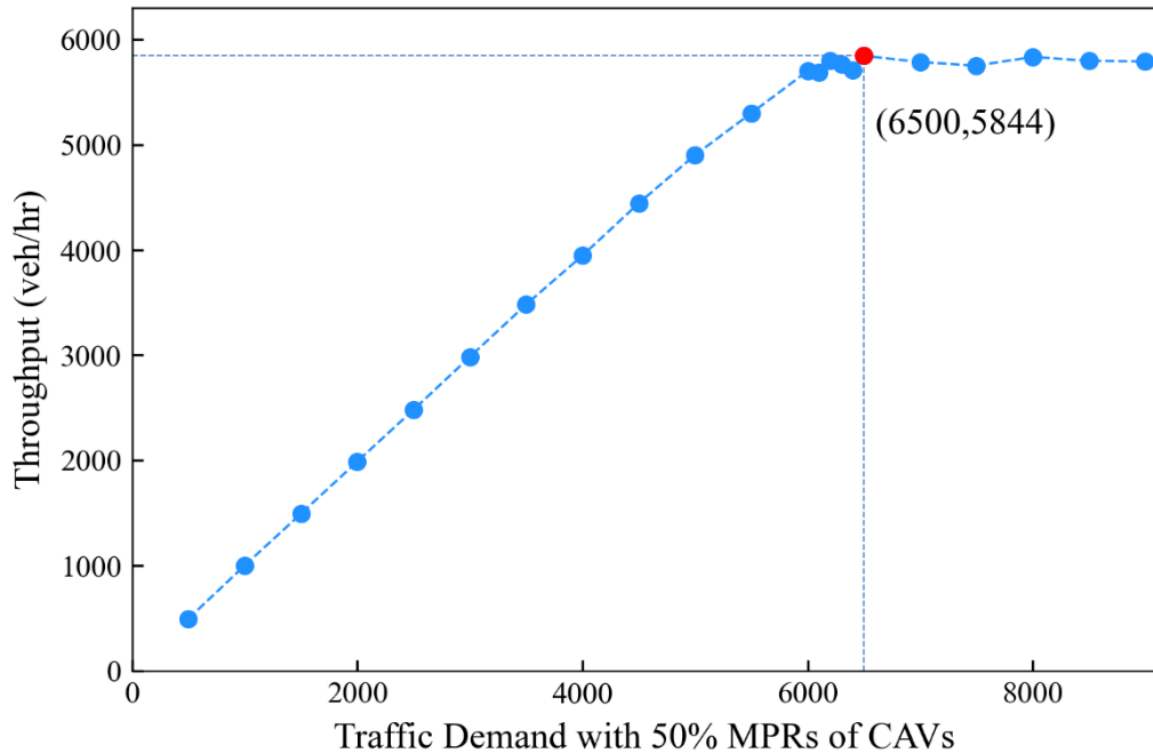


Figure 70. Traffic throughput under 50% MPRs of CAVs

Table 40. Intersection system performance under 50% MPRs of CAVs

Traffic demand	Total waiting time (s)	Average waiting time (s)	Total CO2 (kg)	Avg. CO2 (kg)	Total Fuel (L)	Avg. Fuel (L)	Throughput
500	12060.6	24.12	107.176	0.214	46.072	0.092	494
1000	23763.7	23.76	214.843	0.215	92.354	0.092	1000
1500	33516.9	22.34	312.427	0.208	134.302	0.09	1492
2000	44587	22.29	416.301	0.208	178.954	0.089	1988
2500	56755.8	22.7	520.847	0.208	223.895	0.09	2480
3000	67746.4	22.58	624.098	0.208	268.279	0.089	2982
3500	89678.3	25.62	755.371	0.216	324.709	0.093	3480
4000	120043.2	30.01	901.362	0.225	387.466	0.097	3945
4500	164862.3	36.64	1080.843	0.24	464.62	0.103	4442
5000	263926.5	52.79	1364.498	0.273	586.557	0.117	4900
5500	416545.8	75.74	1728.447	0.314	743.012	0.135	5299
6000	633027.3	105.5	2244.615	0.374	964.903	0.161	5698
6100	708610.1	116.17	2413.281	0.396	1037.41	0.17	5684
6200	735525.3	118.63	2456.849	0.396	1056.139	0.17	5797
6300	837428.6	132.93	2707.048	0.43	1163.697	0.185	5765
6400	896155.6	140.02	2933.63	0.458	1261.102	0.197	5709
6500	906076.3	139.4	3001.592	0.462	1290.318	0.199	5844
7000	1098372	156.91	3568.187	0.51	1533.893	0.219	5784
7500	1202127	160.28	3832.733	0.511	1647.62	0.22	5750
8000	1207118	150.89	3924.905	0.491	1687.244	0.211	5833
8500	1258237	148.03	3985.794	0.469	1713.42	0.202	5796
9000	1284466	142.72	4005.16	0.445	1721.746	0.191	5789

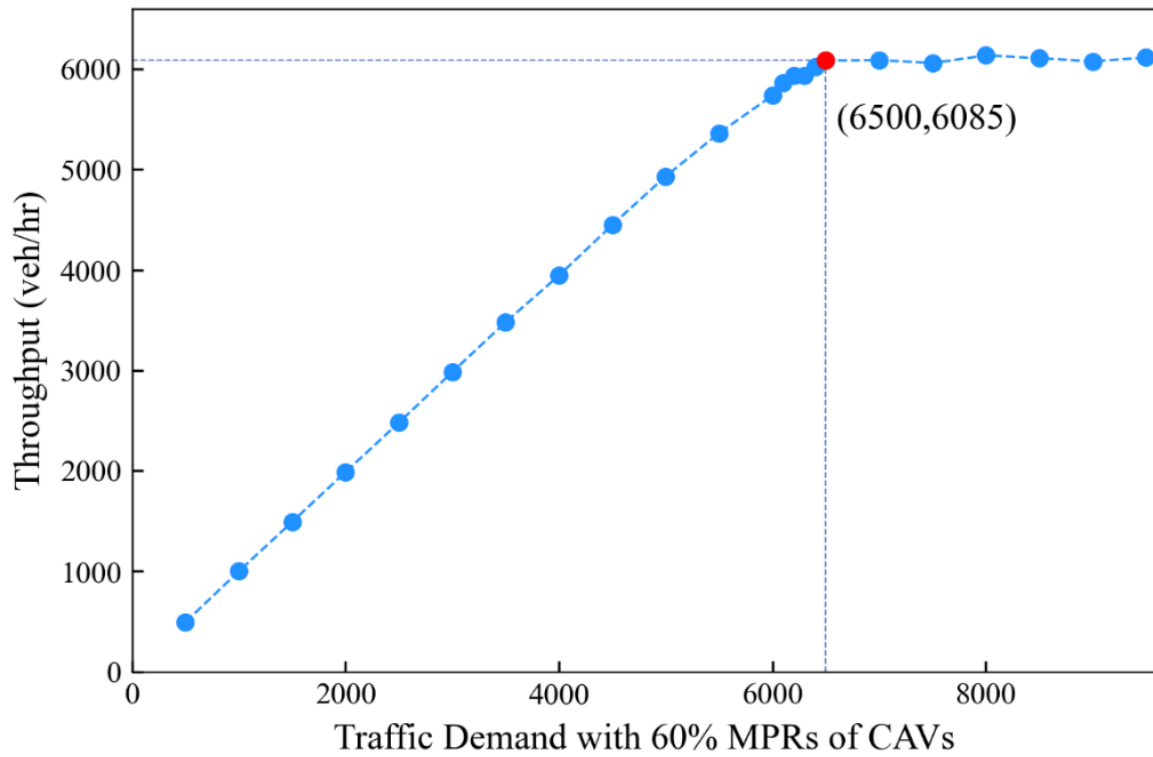


Figure 71. Traffic throughput under 60% MPRs of CAVs

Table 41. Intersection system performance under 60% MPRs of CAVs

Traffic demand	Total waiting time (s)	Average waiting time (s)	Total CO2 (kg)	Avg. CO2 (kg)	Total Fuel (L)	Avg. Fuel (L)	Throughput
500	12108.3	24.22	107.291	0.215	46.121	0.092	494
1000	23964.1	23.96	216.069	0.216	92.881	0.093	1000
1500	33914	22.61	314.82	0.21	135.331	0.09	1492
2000	44936.4	22.47	419.06	0.21	180.14	0.09	1988
2500	57560.7	23.02	526.73	0.211	226.423	0.091	2480
3000	68203.2	22.73	629.285	0.21	270.508	0.09	2983
3500	88706.7	25.34	757.314	0.216	325.544	0.093	3480
4000	111917.3	27.98	888.014	0.222	381.728	0.095	3944
4500	145627.1	32.36	1046.573	0.233	449.888	0.1	4449
5000	210443.9	42.09	1269.429	0.254	545.688	0.109	4932
5500	348080.5	63.29	1622.13	0.295	697.307	0.127	5362
6000	534524.2	89.09	2067.304	0.345	888.679	0.148	5736
6100	554246.6	90.86	2117.071	0.347	910.073	0.149	5863
6200	563689.1	90.92	2167.553	0.35	931.774	0.15	5936
6300	707190.6	112.25	2434.259	0.386	1046.427	0.166	5934
6400	748938.7	117.02	2545.784	0.398	1094.37	0.171	6020
6500	787004.7	121.08	2662.238	0.41	1144.432	0.176	6085
7000	1120209	160.03	3463.39	0.495	1488.838	0.213	6090
7500	1277734	170.36	3829.71	0.511	1646.318	0.22	6059
8000	1299482	162.44	3998.456	0.5	1718.86	0.215	6136
8500	1362942	160.35	4075.358	0.479	1751.92	0.206	6108
9000	1372033	152.45	4120.255	0.458	1771.221	0.197	6077
9500	1371877	144.41	4163.756	0.438	1789.921	0.188	6114

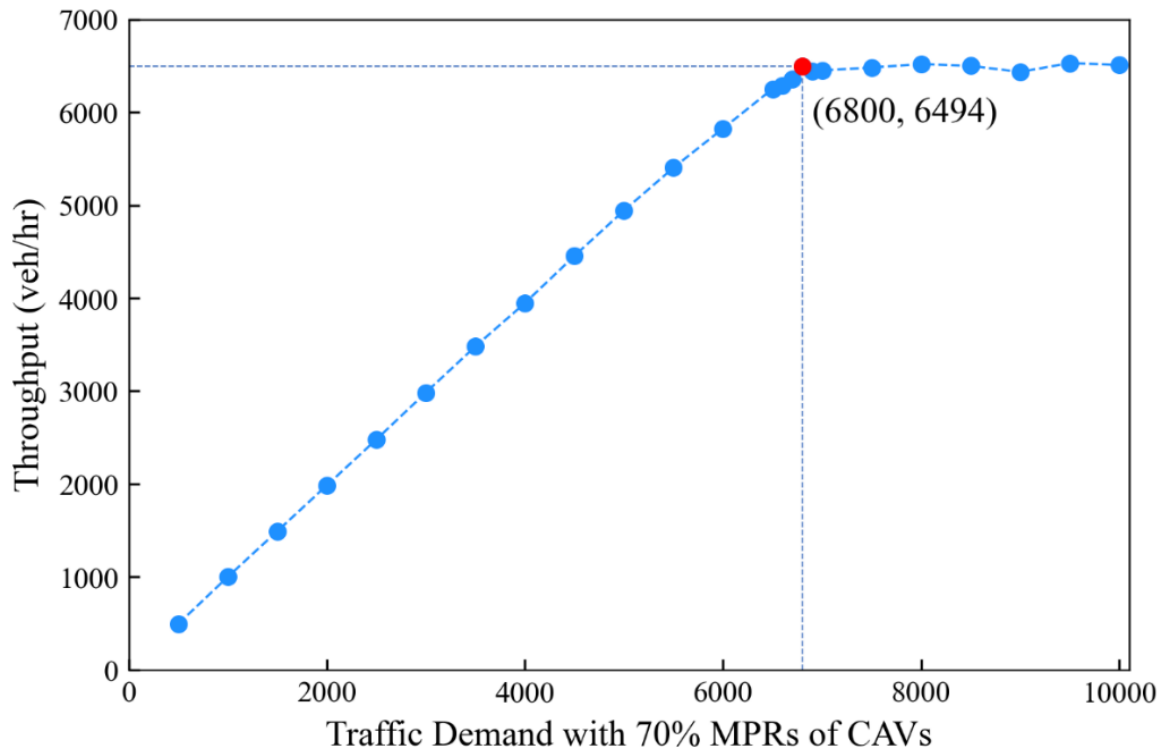


Figure 72. Traffic throughput under 70% MPRs of CAVs

Table 42. Intersection system performance under 70% MPRs of CAVs

Traffic demand	Total waiting time (s)	Average waiting time (s)	Total CO2 (kg)	Avg. CO2 (kg)	Total Fuel (L)	Avg. Fuel (L)	Throughput
500	12172.8	24.35	107.818	0.216	46.348	0.093	494
1000	24044	24.04	217.068	0.217	93.31	0.093	1000
1500	34320.5	22.88	317.418	0.212	136.448	0.091	1492
2000	44958.2	22.48	421.419	0.211	181.154	0.091	1985
2500	58201.9	23.28	532.274	0.213	228.807	0.092	2479
3000	68884.5	22.96	635.887	0.212	273.346	0.091	2984
3500	87722.3	25.06	761.196	0.217	327.213	0.093	3481
4000	109287.5	27.32	888.818	0.222	382.074	0.096	3947
4500	132305.2	29.4	1024.559	0.228	440.424	0.098	4455
5000	193135.7	38.63	1248.29	0.25	536.601	0.107	4943
5500	306379.9	55.71	1557.082	0.283	669.344	0.122	5404
6000	442413.9	73.74	1924.879	0.321	827.452	0.138	5826
6500	549531.4	84.54	2224.695	0.342	956.337	0.147	6252
6600	698908.7	105.9	2521.003	0.382	1083.716	0.164	6284
6700	754646	112.63	2632.851	0.393	1131.796	0.169	6357
6800	734282.3	107.98	2636.286	0.388	1133.273	0.167	6494
6900	904866.8	131.14	2942.994	0.427	1265.123	0.183	6443
7000	950393.7	135.77	3082.97	0.44	1325.296	0.189	6451
7500	1303577	173.81	3843.435	0.512	1652.214	0.22	6482
8000	1398990	174.87	4118.533	0.515	1770.475	0.221	6519
8500	1452932	170.93	4251.536	0.5	1827.652	0.215	6500
9000	1496969	166.33	4310.072	0.479	1852.818	0.206	6435
9500	1506604	158.59	4390.466	0.462	1887.378	0.199	6530
10000	1586827	158.68	4431.992	0.443	1905.229	0.191	6509

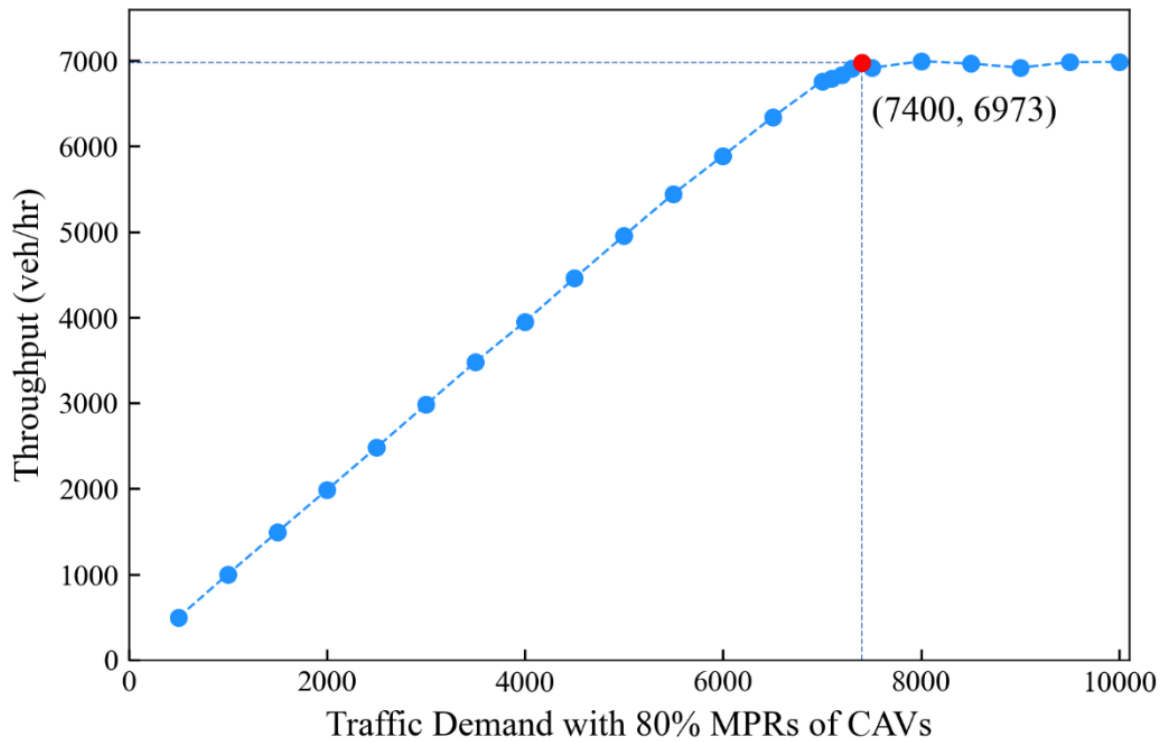


Figure 73. Traffic throughput under 80% MPRs of CAVs

Table 43. Intersection system performance under 80% MPRs of CAVs

Traffic demand	Total waiting time (s)	Average waiting time (s)	Total CO2 (kg)	Avg. CO2 (kg)	Total Fuel (L)	Avg. Fuel (L)	Throughput
500	12267.5	24.54	108.345	0.217	46.574	0.093	494
1000	24195.7	24.2	218.184	0.218	93.79	0.094	1000
1500	34777.2	23.18	320.629	0.214	137.828	0.092	1492
2000	45725.1	22.86	426.936	0.213	183.525	0.092	1984
2500	58344.4	23.34	536.409	0.215	230.584	0.092	2479
3000	69429.6	23.14	641.979	0.214	275.965	0.092	2981
3500	87971.4	25.13	766.617	0.219	329.543	0.094	3480
4000	104918.9	26.23	887.318	0.222	381.429	0.095	3950
4500	127484.8	28.33	1024.659	0.228	440.467	0.098	4459
5000	177048.8	35.41	1224.533	0.245	526.388	0.105	4955
5500	253379	46.07	1471.602	0.268	632.597	0.115	5445
6000	361557.5	60.26	1789.403	0.298	769.213	0.128	5890
6500	454979.3	70	2070.006	0.318	889.839	0.137	6339
7000	670225.3	95.75	2583.741	0.369	1110.684	0.159	6762
7100	673483.8	94.86	2610.83	0.368	1122.329	0.158	6791
7200	879506.9	122.15	3023.953	0.42	1299.924	0.181	6835
7300	904715.7	123.93	3094.031	0.424	1330.049	0.182	6909
7400	955250	129.09	3204.906	0.433	1377.712	0.186	6973
7500	1161934	154.92	3590.499	0.479	1543.474	0.206	6916
8000	1383276	172.91	4098.508	0.512	1761.862	0.22	6994
8500	1564170	184.02	4472.95	0.526	1922.83	0.226	6967
9000	1634014	181.56	4582.256	0.509	1969.821	0.219	6919
9500	1643344	172.98	4625.663	0.487	1988.481	0.209	6983
10000	1718129	171.81	4760.845	0.476	2046.594	0.205	6985

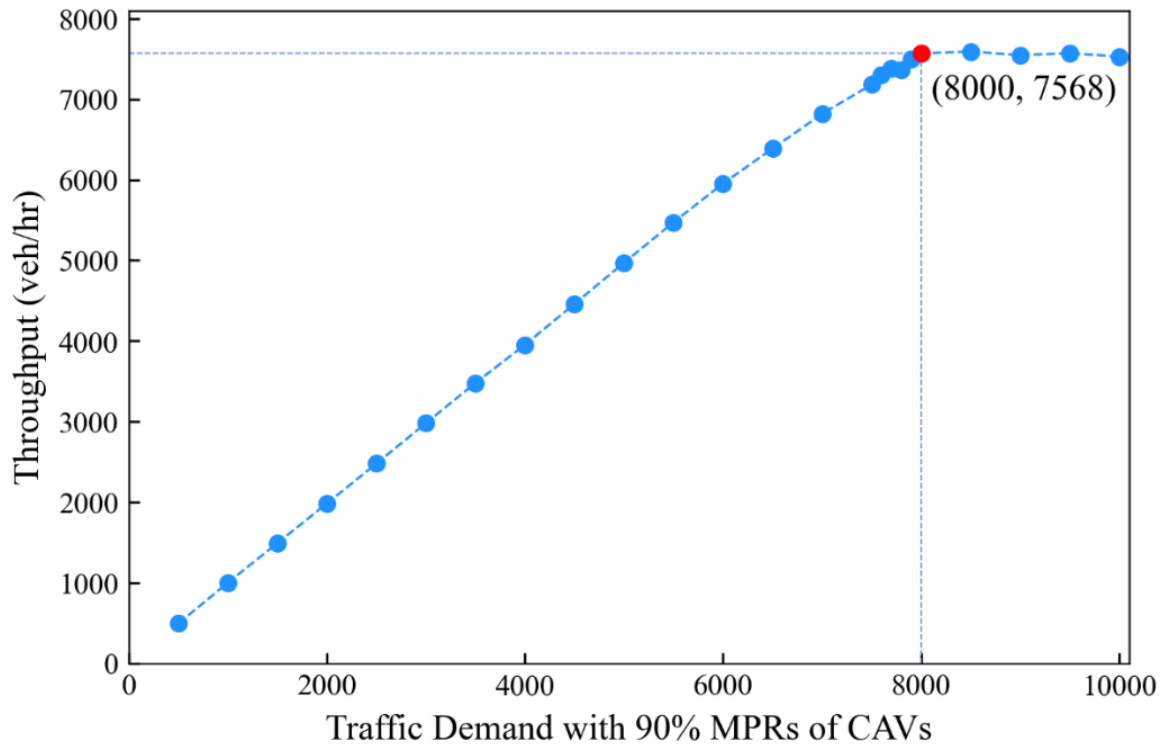


Figure 74. Traffic throughput under 90% MPRs of CAVs

Table 44. Intersection system performance under 90% MPRs of CAVs

Traffic demand	Total waiting time (s)	Average waiting time (s)	Total CO2 (kg)	Avg. CO2 (kg)	Total Fuel (L)	Avg. Fuel (L)	Throughput
500	12365	24.73	108.974	0.218	46.844	0.094	494
1000	24416.1	24.42	219.995	0.22	94.569	0.095	1000
1500	35192.3	23.46	323.214	0.215	138.939	0.093	1492
2000	46261	23.13	430.613	0.215	185.106	0.093	1984
2500	59334.6	23.73	542.593	0.217	233.243	0.093	2479
3000	70241.8	23.41	651.515	0.217	280.065	0.093	2981
3500	88223.6	25.21	774.437	0.221	332.905	0.095	3480
4000	101536.6	25.38	888.003	0.222	381.723	0.095	3953
4500	119939.3	26.65	1017.865	0.226	437.547	0.097	4460
5000	149723.2	29.94	1171.512	0.234	503.595	0.101	4971
5500	189801.2	34.51	1354.243	0.246	582.146	0.106	5473
6000	256582	42.76	1596.579	0.266	686.321	0.114	5955
6500	376795.7	57.97	1944.982	0.299	836.092	0.129	6387
7000	512583.1	73.23	2324.09	0.332	999.063	0.143	6818
7500	758656.6	101.15	2924.99	0.39	1257.379	0.168	7182
7600	722370.1	95.05	2881.637	0.379	1238.742	0.163	7298
7700	766343.1	99.53	2984.247	0.388	1282.852	0.167	7385
7800	976699.7	125.22	3413.842	0.438	1467.529	0.188	7367
7900	958146.9	121.28	3444.773	0.436	1480.824	0.187	7496
8000	1008473	126.06	3539.99	0.442	1521.757	0.19	7568
8500	1430163	168.25	4384.002	0.516	1884.586	0.222	7592
9000	1731755	192.42	4915.793	0.546	2113.198	0.235	7547
9500	1771778	186.5	5019.404	0.528	2157.739	0.227	7571
10000	1836707	183.67	5227.749	0.523	2247.303	0.225	7528

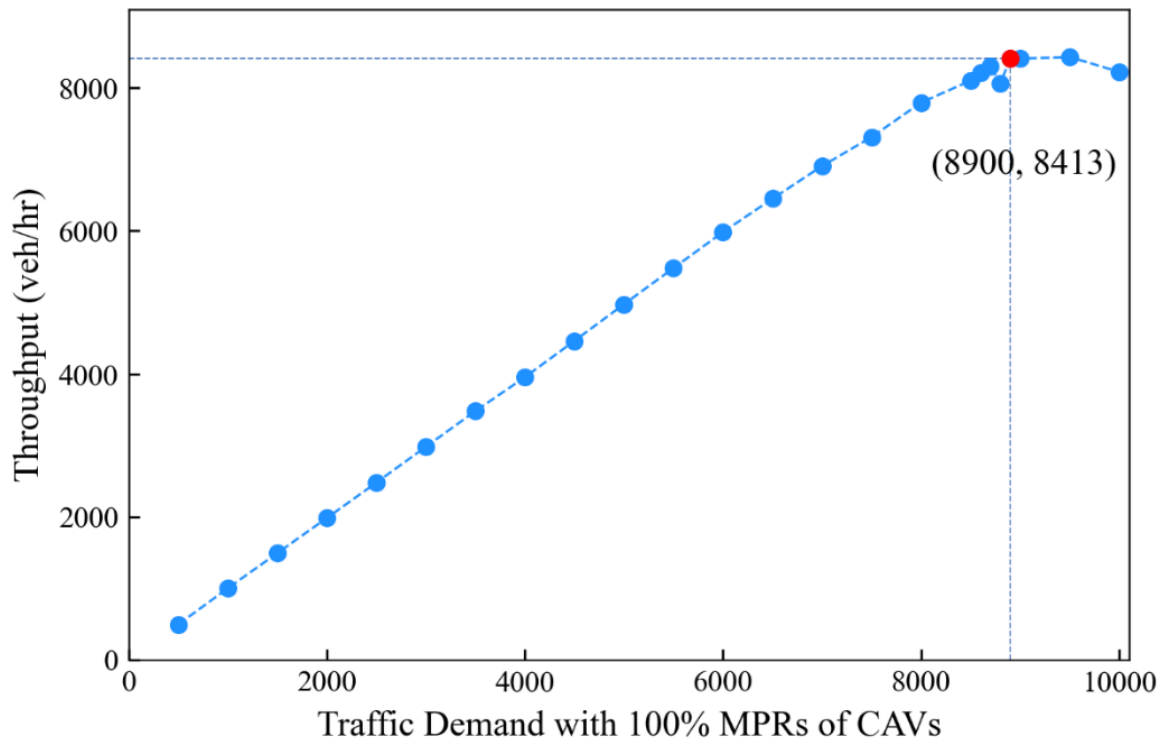


Figure 75. Traffic throughput under 100% MPRs of CAVs

Table 45. Intersection system performance under 100% MPRs of CAVs

Traffic demand	Total waiting time (s)	Average waiting time (s)	Total CO2 (kg)	Avg. CO2 (kg)	Total Fuel (L)	Avg. Fuel (L)	Throughput
500	12433.4	24.87	109.39	0.219	47.023	0.094	494
1000	24632.1	24.63	221.223	0.221	95.097	0.095	1000
1500	35635.1	23.76	326.285	0.218	140.259	0.094	1492
2000	46761.4	23.38	435.096	0.218	187.033	0.094	1983
2500	59958.3	23.98	549.445	0.22	236.188	0.094	2479
3000	70636	23.55	657.291	0.219	282.548	0.094	2980
3500	89279.1	25.51	787.178	0.225	338.382	0.097	3479
4000	101055.1	25.26	899.762	0.225	386.778	0.097	3954
4500	117777.1	26.17	1025.093	0.228	440.654	0.098	4462
5000	141176.6	28.24	1168.984	0.234	502.508	0.101	4974
5500	166383.2	30.25	1318.526	0.24	566.792	0.103	5481
6000	190778.7	31.8	1462.993	0.244	628.894	0.105	5984
6500	285049.8	43.85	1783.747	0.274	766.779	0.118	6451
7000	401423.2	57.35	2159.492	0.308	928.305	0.133	6908
7500	573743.6	76.5	2663.693	0.355	1145.051	0.153	7313
8000	634724.7	79.34	2901.644	0.363	1247.341	0.156	7796
8500	887167.1	104.37	3585.327	0.422	1541.244	0.181	8103
8600	916726.6	106.6	3675.872	0.427	1580.168	0.184	8217
8700	1054315	121.19	4036.668	0.464	1735.269	0.199	8306
8800	1151207	130.82	4238.876	0.482	1822.195	0.207	8060
8900	1157348	130.04	4323.411	0.486	1858.534	0.209	8413
9000	1349751	149.97	4776.651	0.531	2053.375	0.228	8411
9500	1756586	184.9	5701.14	0.6	2450.8	0.258	8433
10000	1910148	191.01	6027.113	0.603	2590.932	0.259	8226

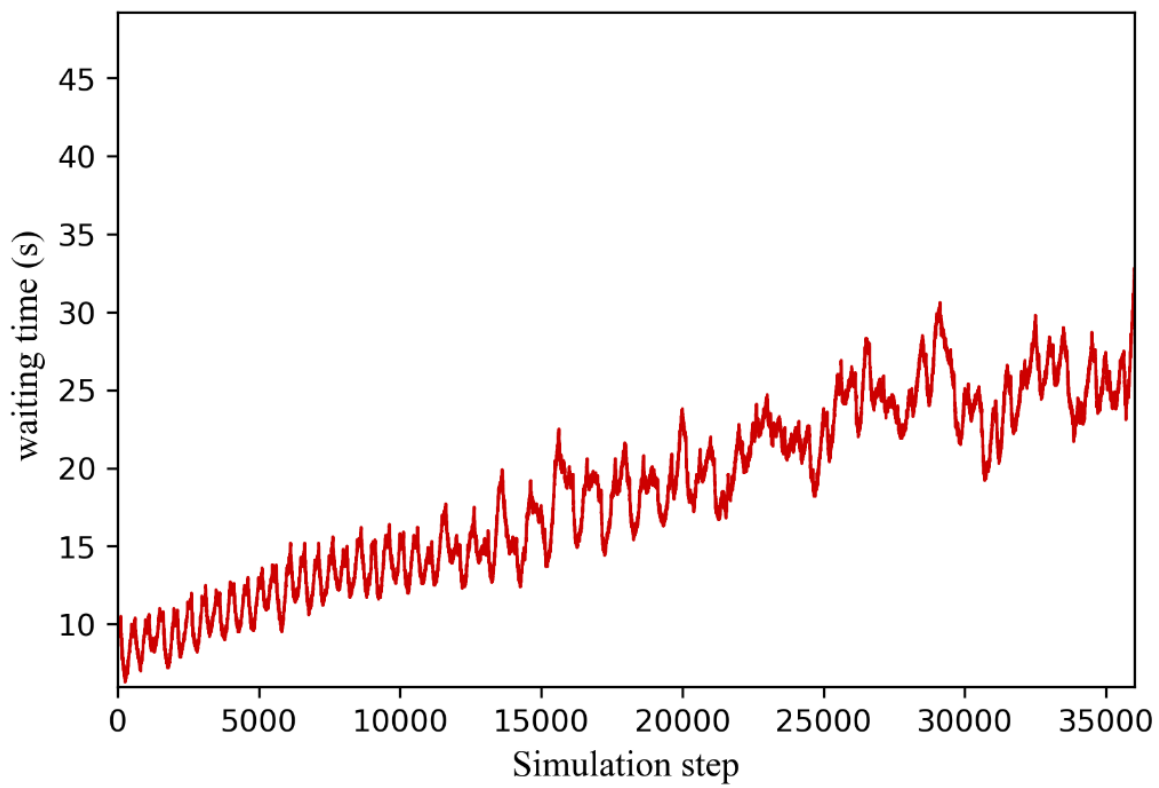


Figure 76. Traffic waiting time per simulation step

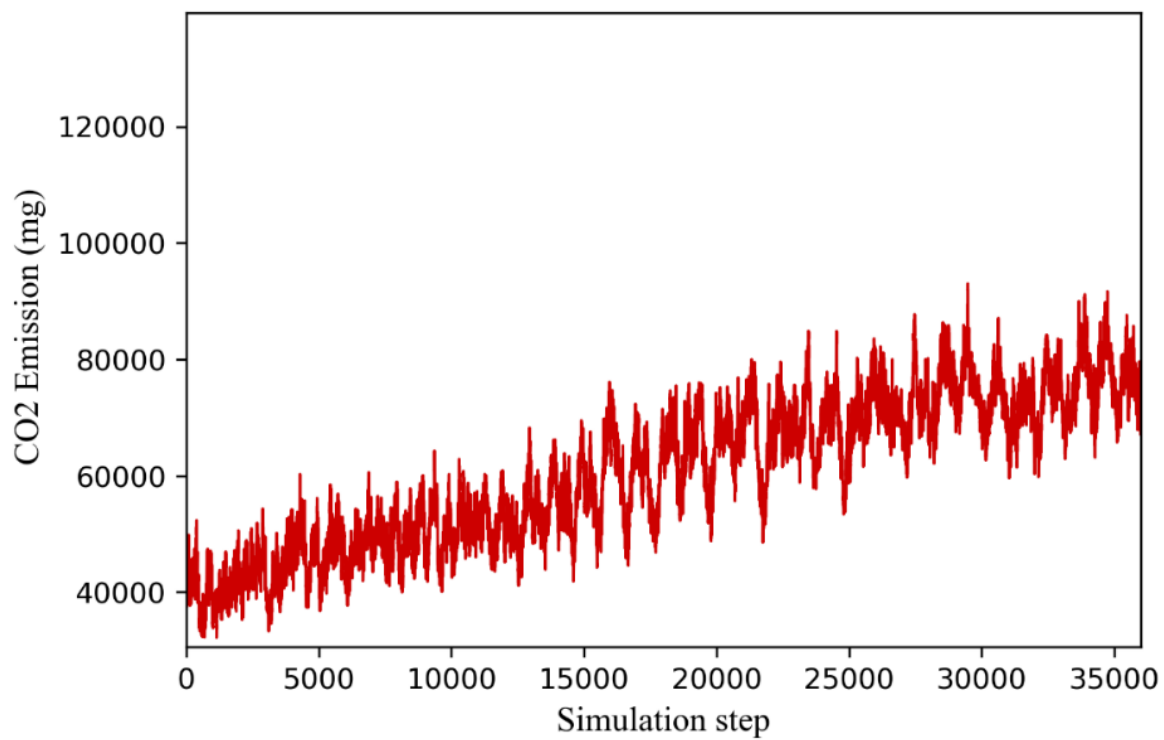


Figure 77. Traffic CO2 emission per simulation step

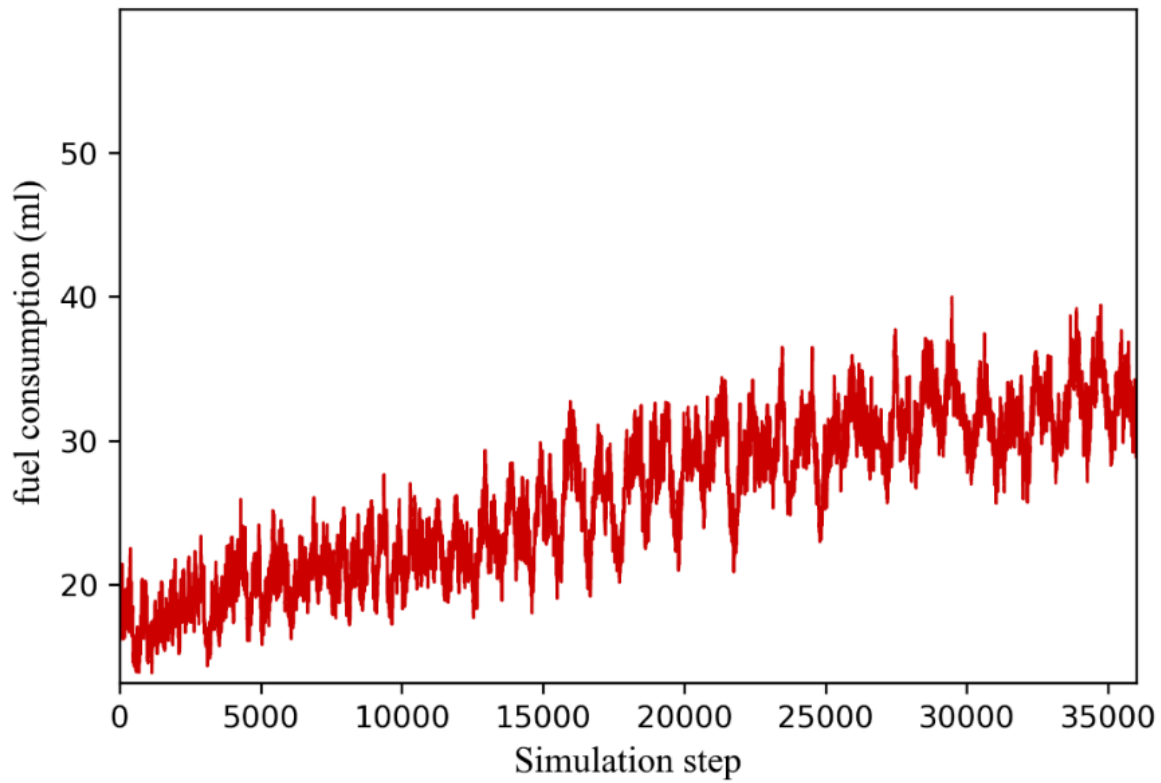


Figure 78. Traffic fuel consumption per simulation step

Table 46. Traffic performance under saturated traffic flow with different MPRs of CAVs

MPR	Traffic demand	Total waiting time (s)	Average waiting time (s)	Total CO2 (kg)	Avg. CO2 (kg)	Total Fuel (L)	Avg. Fuel (L)	Through-put	Change rate
0	5400	658796.4	122	2180.46	0.40	937.3	0.174	4938	
0.1	5600	697819	124.61	2385.62	0.43	1025.52	0.18	5047	1.02
0.2	5600	695985.4	124.28	2282.99	0.41	981.403	0.18	5155	1.04
0.3	6100	860257.7	141.03	2922.06	0.48	1256.132	0.21	5339	1.08
0.4	6200	848790.4	136.9	2854.67	0.46	1227.158	0.2	5565	1.13
0.5	6500	906076.3	139.4	3001.59	0.46	1290.318	0.2	5844	1.18
0.6	6500	787004.7	121.08	2662.24	0.41	1144.432	0.18	6085	1.23
0.7	6800	734282.3	107.98	2636.29	0.39	1133.273	0.17	6494	1.32
0.8	7400	955250	129.09	3204.91	0.43	1377.712	0.19	6973	1.41
0.9	8000	1008473.3	126.06	3539.99	0.44	1521.757	0.19	7568	1.53
1	8900	1157348.1	130.04	4323.41	0.49	1858.534	0.21	8413	1.70

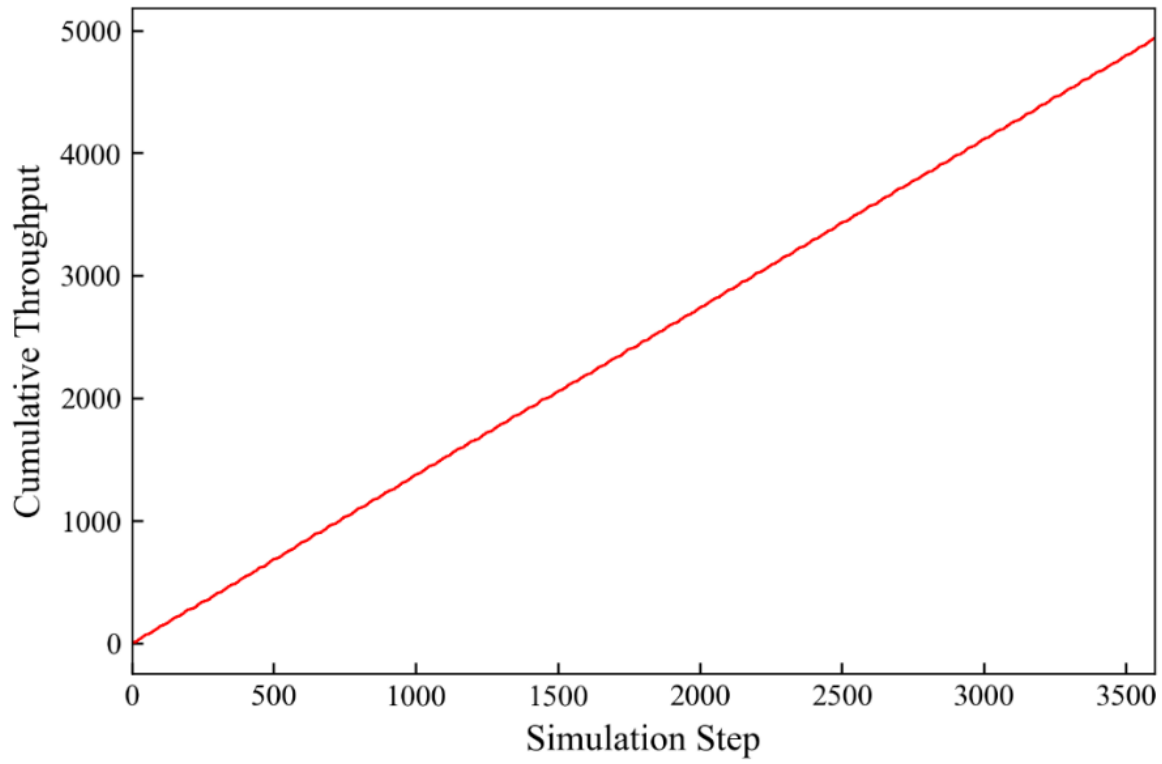


Figure 79. Traffic cumulative throughput

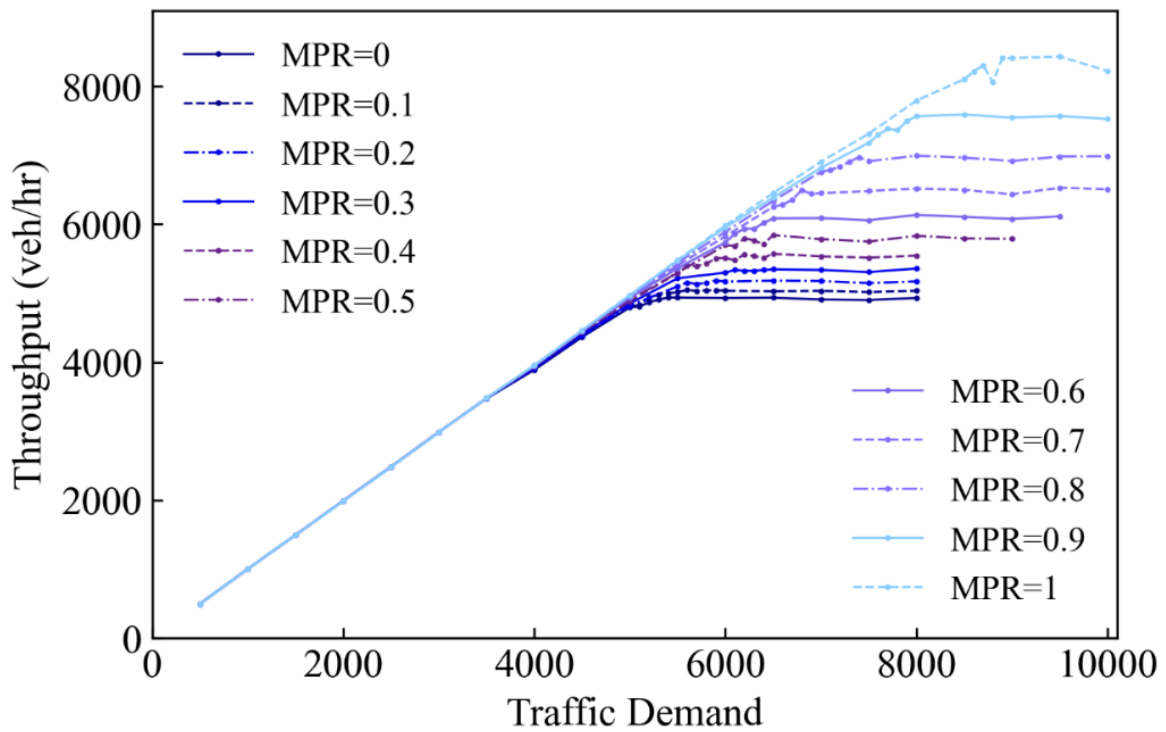


Figure 80. Traffic throughput under different MPRs of CAVs

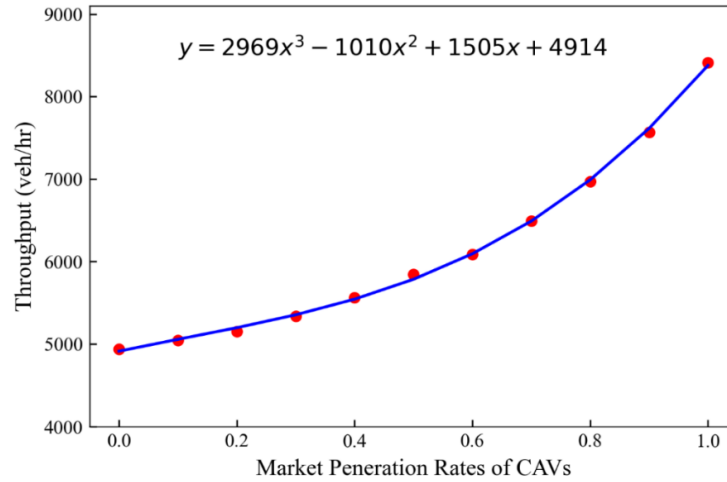


Figure 81. Maximum throughput under different MPRs of CAVs

MPRs of CAVs and increases rapidly after 70% MPRs of CAVs. With the increase of the traffic throughput, the total CO₂ emission, total fuel consumption, and total waiting time also increase significantly after 70% MPRs of CAVs.

$$CO_2 = 9003MPR^3 - 11800MPR^2 + 5023MPR + 2052 \quad (B.31)$$

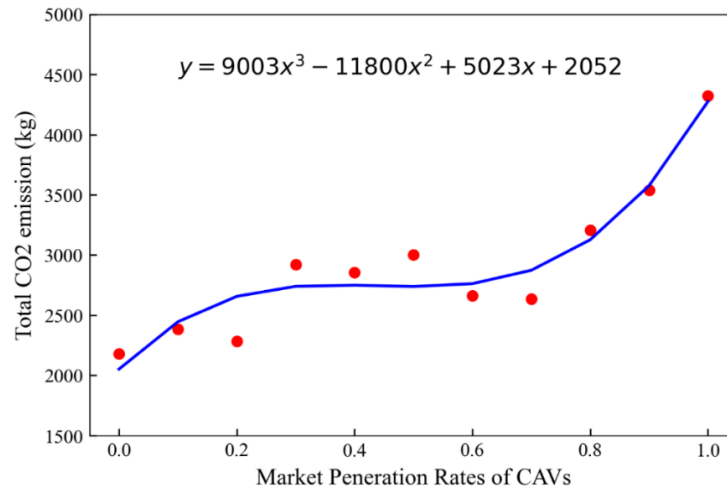


Figure 82. Total CO₂ emission of the saturated traffic flow with different MPRs of CAVs

$$Fuel = 3870MPR^3 - 5074MPR^2 + 2159MPR + 882.1 \quad (B.32)$$

$$WaitingTime = 2.166MPR^3 - 2.96MPR^2 + 1.332MPR + 0.6208 \quad (B.33)$$

B.4.3 Impacts of CAV Penetration Rates under Fixed Traffic Demands

B.4.3.1 Hypothetical isolated Intersection

In this part, this study investigates the impacts of CAV penetration rates on the intersection with fixed traffic demands. As shown in Figure reffig:5-23, with the increase of CAV penetration rates, the intersection capacity could increase from the C_{HDV} (intersection capacity with 100% HDVs) into C_{CAV} (intersection capacity with 100%

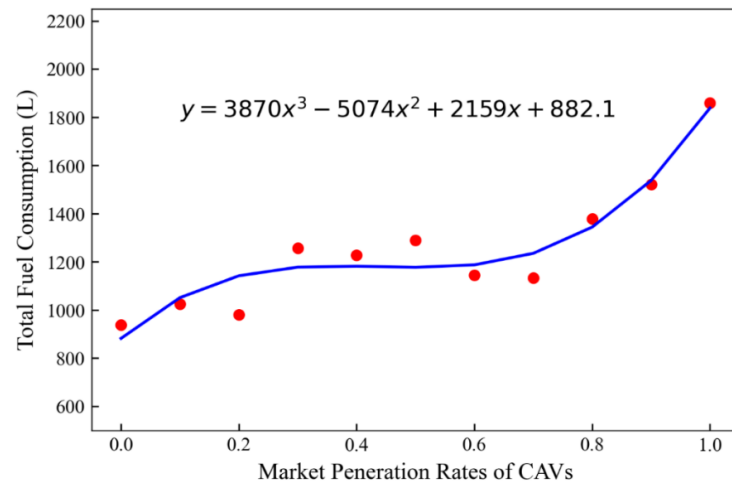


Figure 83. Total fuel consumption of the saturated traffic flow with different MPRs of CAVs

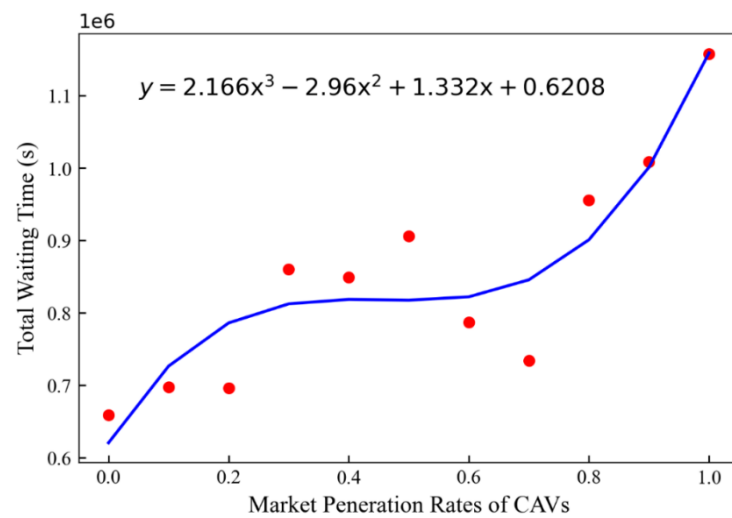


Figure 84. Total waiting time of the saturated traffic flow with different MPRs of CAVs

CAVs). Hence, the traffic demand condition could be divided into two main ranges, i.e., $0 < \text{Demand} < C_{HDV}$ and $C_{HDV} < \text{Demand} \leq C_{CAV}$. For scenarios with fixed traffic demands between these two sections, the impacts of the CAV penetration rates on the intersection are also supposed to be different under different traffic demand levels. In this case, the hypothetical isolated intersection is first selected as a basic case study for the investigation of the impacts of CAV penetration rates under fixed traffic demand scenarios. In this part, the total waiting time is selected as the

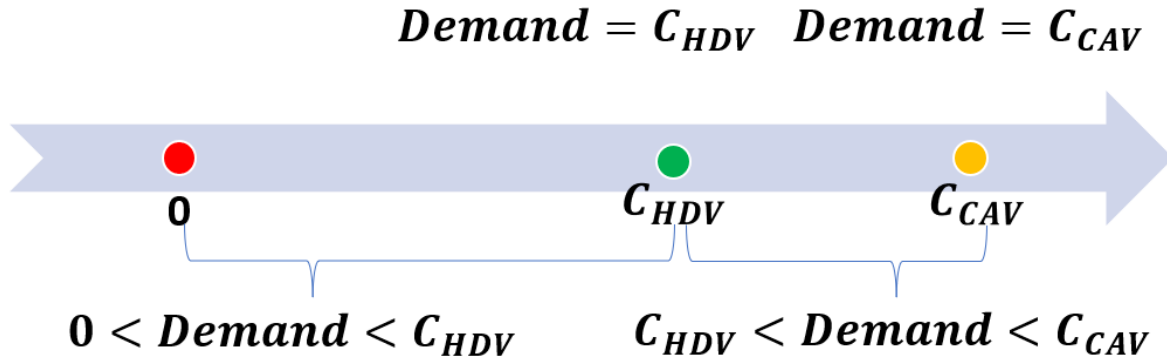


Figure 85. Traffic demand conditions of the intersection with different MPRs of CAVs

intersection performance criterion as it could both indicate the traffic volume and stopping time. The total waiting time is calculated by the summation of the time for vehicles when the vehicle speed is less than 0.1 m/s. Scenarios with different traffic demands between 0 to C_{CAV} are investigated to analyze the impacts of CAV penetration rates. As calculated in section 5.2, the C_{CAV} for this isolated intersection is 1.7 times of the C_{HDV} .

Figure 86 indicates the variation tendency of the total waiting time under different MPRs of CAVs with different fixed traffic demand levels. According to the general tendency of the total waiting time, the traffic demands could be segmented into three levels. For Figures 5-24 (1) and (2) with curves in red color and circle points, the traffic demands are $0.2 C_{HDV}$ and $0.6 C_{HDV}$, respectively. Both curves indicate a slightly increasing trend in the total waiting time with the increase of the CAV penetration rates. For Figures 5-24 (3) to (6) with curves in green color and triangle points, the traffic demands are $0.65 C_{HDV}$, $0.7 C_{HDV}$, $0.8 C_{HDV}$, and C_{HDV} , respectively. All of the curves present a decreasing trend in the total waiting time with the increase of CAV penetration rates. For Figures 5-24 (7) to (10) with curves in orange color and square points, the traffic demands are $1.1 C_{HDV}$, $1.3 C_{HDV}$, $1.5 C_{HDV}$, and $1.7 C_{HDV}$, respectively. All curves indicate a stable value or an increasing trend in the total waiting time at first. Then the total waiting time decreases with the increase of the CAV penetration rates after certain MPRs of CAVs.

In summary, according to the variation tendency of the total waiting time under different MPRs of CAVs, the traffic demands for the isolated intersection could be mainly classified into three ranges. Note that such segmentation ranges could vary across different intersection layouts. The traffic demand segmentation of this hypothetical isolated intersection is illustrated in Figure 5-25. Also, the features of the three variation tendencies are summarized as follows.

- (1) $0 < \text{Demand} \leq 0.6 C_{HDV}$: the total waiting time increases slightly with the increase of CAV penetration rates (curves in red color with circle points);
- (2) $0.6 C_{HDV} < \text{Demand} < C_{HDV}$: the total waiting time decreases accordingly with the increase of CAV penetration (curves in green color with triangle points);
- (3) $C_{HDV} < \text{Demand} < C_{CAV}$: the total waiting time decreases only after a certain CAV penetration rate (curves in orange color with square points).

B.4.3.2 Isolated Intersection in Charlotte, NC

As introduced in Chapters 3 and 4, an isolated intersection in Charlotte, NC is selected to investigate the impacts of CAV penetration rates on the intersection with fixed traffic demands. The layout of the isolated intersection is shown in Figures 88. The pre-timed signal schemes and basic traffic demands are all described in Section 4.4.1.

Figure 89 presents the total waiting time of the isolated intersection under different MPRs of CAVs. In Figure 89 (1), with the basic traffic demands (real-world data), the total waiting time decreases with the increase of CAV penetration rates. This tendency is in accord with the second variation stage as introduced in Figure 5-25. Also, this study tests the variation tendency of the total waiting time in other traffic demand scenarios. The basic traffic

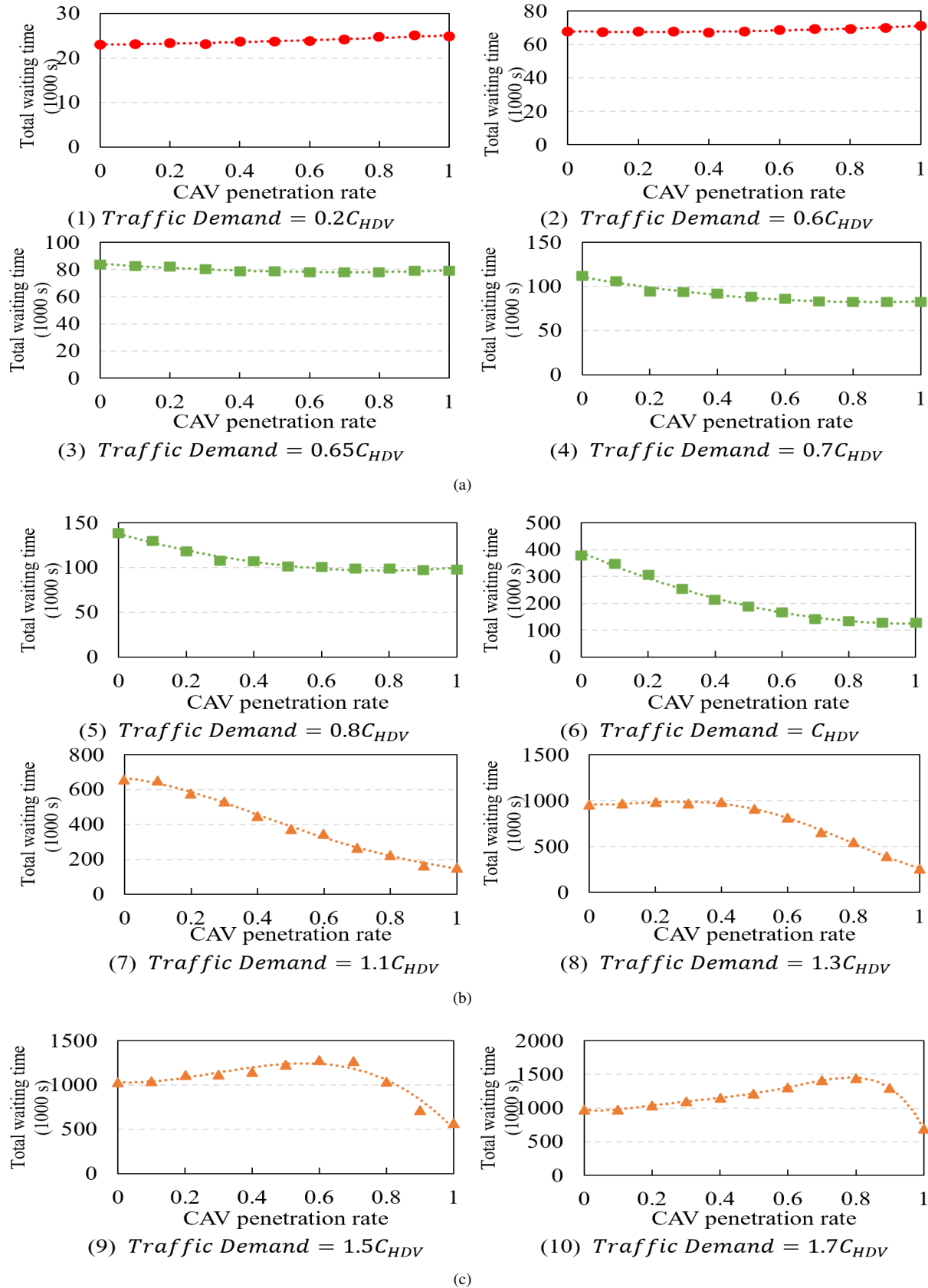


Figure 86. Impacts of CAV penetration rates on the total waiting time under different traffic demand levels

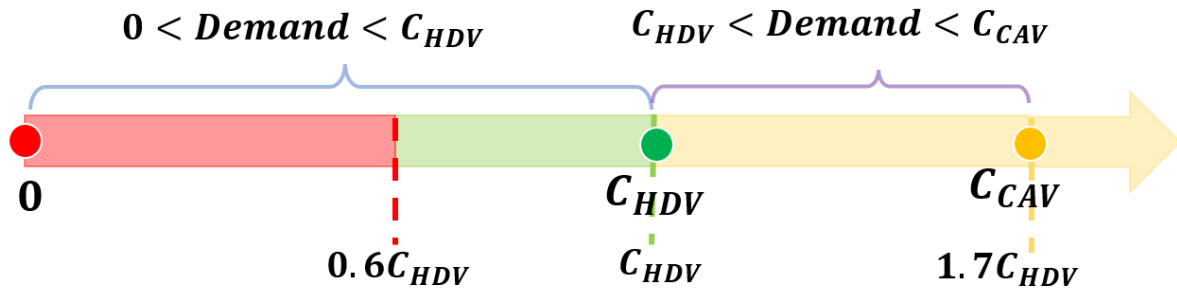


Figure 87. Three traffic demand ranges with different CAV impact trends on the total waiting time for the hypothetical isolated intersection

demand is increased to 1.5 times as high, and the results are shown in Figures 89 (2). The total waiting time decreases with the increase of the MPRs of CAVs.

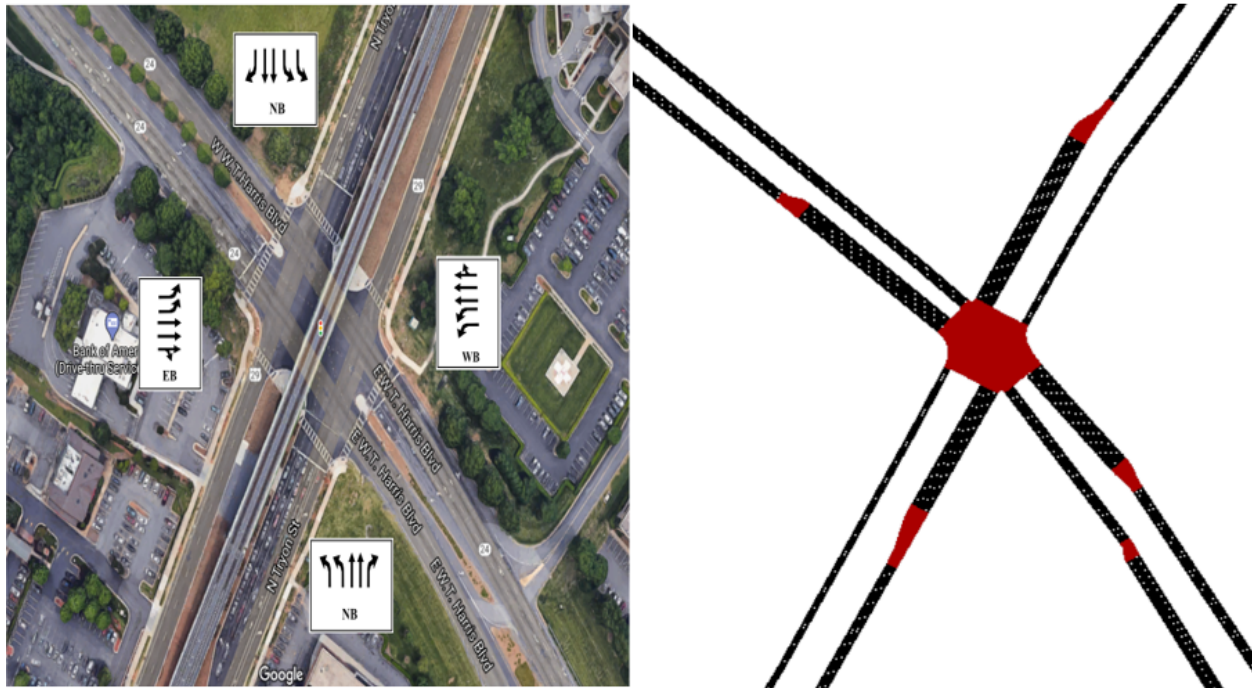


Figure 88. Layout of the isolated intersection in the city of Charlotte, NC

B.4.3.3 Two Adjacent Intersections in Greensboro, NC

As introduced in Chapters 3 and 4, two adjacent intersections in Greensboro, NC are also selected to investigate the impacts of CAV penetration rates on the intersection with fixed traffic demands. The signal phases of the two intersections are coordinated for the main street due to the small distance between these two intersections (106 m). Also, these kinds of adjacent intersections are commonly seen in urban areas and are often analyzed as a whole intersection system. The layout of the two adjacent intersections is shown in Figure 90. The pre-timed signal schemes and basic traffic demands are all described in Section 4.4.2.

Figure 91 indicates the total waiting time of the two adjacent intersections under different MPRs of CAVs. In Figure 91(1), with the basic traffic demands (real-world data), the total waiting time increases slightly with the increase of CAV penetration rates. This tendency is in accord with the first variation stage as introduced in Figure 87. Also, this study tests the variation tendency of the total waiting time in other traffic demand scenarios. The basic traffic demand is increased to 1.5 times as high in Figures 91 (2). The total waiting time decreases with the increase of CAV penetration rates. This indicates the shift of variation tendency from the first stage into the second stage.

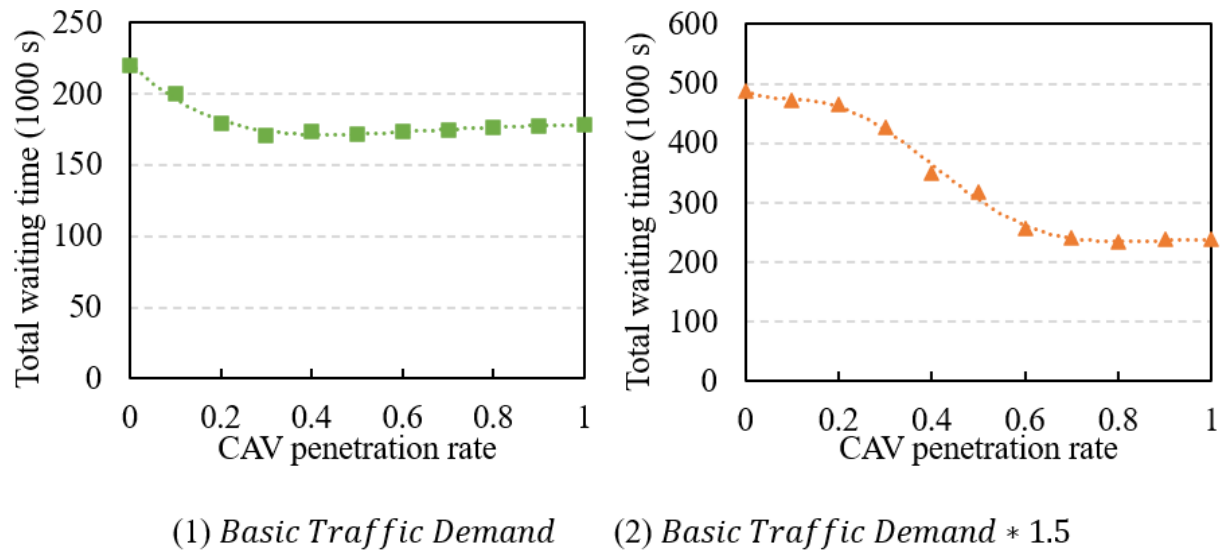


Figure 89. Impacts of CAV penetration rates on the total waiting time of the isolated intersection under different traffic demand levels

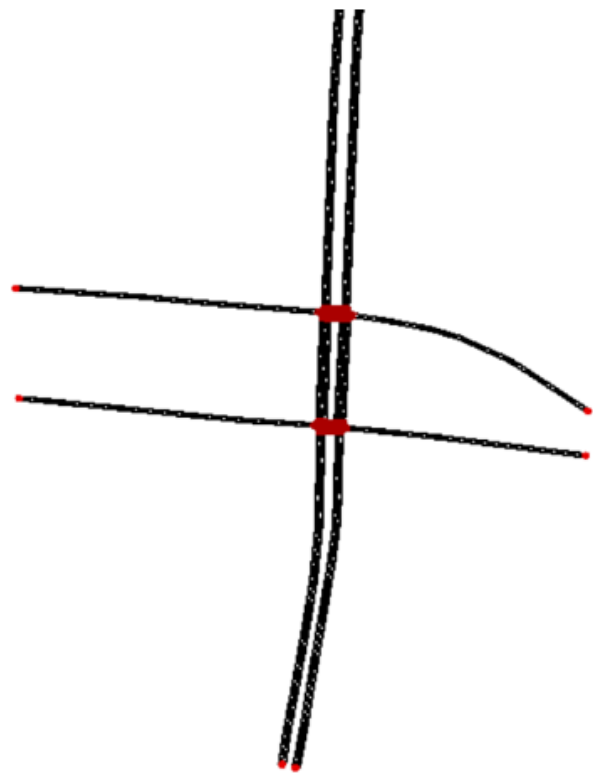


Figure 90. Layout of two adjacent intersections in Greensboro, NC

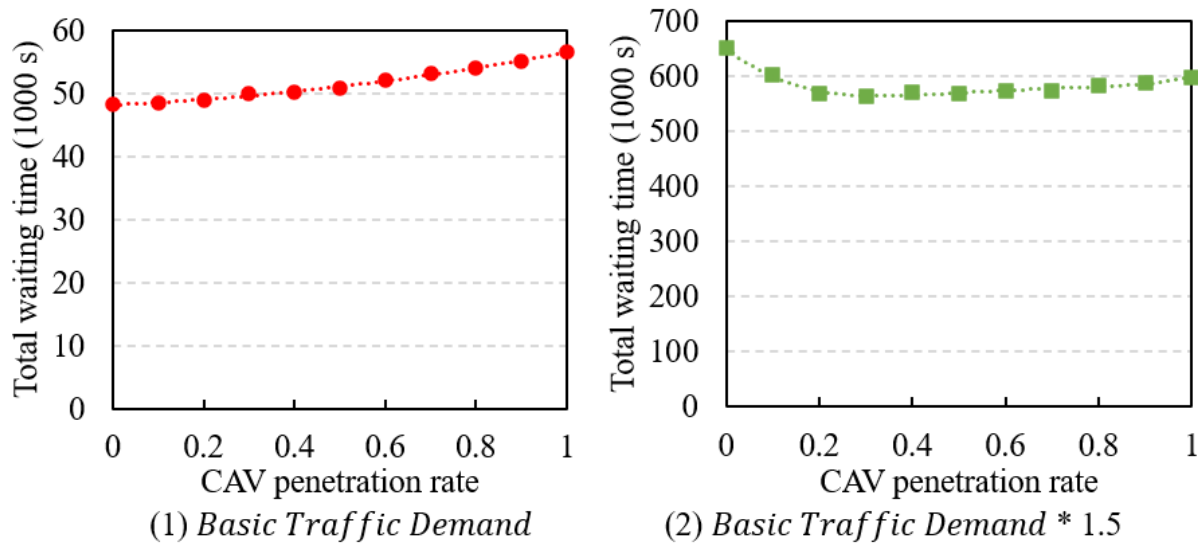


Figure 91. Impacts of CAV penetration rates on the total waiting time of the two-adjacent intersections under different traffic demand levels

B.4.4 Summary

In this chapter, an isolated four-way intersection is utilized to set a basic scenario for the capacity analysis simulation. Both the lane-level and intersection-level intersection capacity are investigated. In the lane-level capacity investigation, adjustment factors for the saturation headway and saturation traffic flow rate for each lane group under different MPRs of CAVs are all calculated. In the intersection-level capacity investigation, the maximum throughput of the intersection under different MPRs of CAVs is calculated. Moreover, the fitting curves and fitting functions for the maximum throughput, total waiting time, total CO₂ emission, and total fuel consumption under different MPRs of CAVs are calibrated and investigated.

After that, this research investigates the impacts of CAV penetration rates on the intersection with fixed traffic demands. Three case studies, including one hypothetical isolated intersection, one isolated intersection in Charlotte, and two adjacent intersections in Greensboro, are analyzed. Results indicate that the benefits of CAV technologies at the intersection require a certain market penetration rate of CAVs and at a certain traffic demand level.

In summary, traffic engineers are expected to be able to directly calculate the intersection capacity under mixed traffic environments by using the adjustment factors documented in this study. The results and the analytical framework of this study could provide theoretical bases and fundamental guidance for transportation researchers and practitioners to better design, plan and operate intersection systems under CAV environments.

B.5 SUMMARY AND CONCLUSIONS

CAVs will have a profound influence on the performance of the currently used and future transportation system, especially for intersections that have complex traffic conditions. Currently, travel demand has been increasing significantly over the years; As a result, traditional intersections are no longer able to effectively handle delays, thus contributing to higher levels of congestion and emissions. As such, there is a critical need to increase the capacity of the intersections and traffic throughput using emerging CAV technologies. Also, traffic planners and engineers are expected to calculate or estimate the intersection capacity considering the implementation of CAVs. However, currently used Highway Capacity Manual methods do not consider the impacts of CAVs on the transportation system. Evaluating the capacity of intersections under the impacts of CAVs is becoming a critical issue to be resolved for transportation planners and engineers. New guidelines for estimating the capacity of intersections, including the consideration of CAV involvement in mixed traffic, need to be established. The impact of CAVs on the intersection system needs to be quantified under different MPRs of CAVs.

To better prepare and guide both intersection planning and operations under different MPRs of CAVs and traffic demands, this research provides an intensive evaluation of the impacts of CAVs on currently used intersection systems, along with an in-depth analysis of intersection capacity adjustments considering varying MPRs of CAVs under different traffic demand situations. The calibration methods and results of intersection capacity adjustment factors for different CAV penetration rates could provide a guideline for transportation engineers/planners to modify

intersection capacity considering the impacts of CAVs and better design, plan, and operate intersection systems under CAV environments. The main objectives of the first part of this research project are to:

- (1). Conduct a comprehensive literature review of the state-of-the-art and state-of-the-practice on CAV technologies and their impacts on the intersection capacity;
- (2). Develop case studies to illustrate these impacts. Considering the impacts of CAVs at intersections. Potential intersections and specific simulation scenarios will be identified for the case study;
- (3). Create simulation methods for different vehicles and estimate the intersection capacity under different MPRs of CAVs; and
- (4). Analyze the impacts of the CAV technologies on the intersection capacity and provide guidelines on the intersection capacity adjustments for engineer applications.

This research provides a comprehensive review of the current state-of-the-art and state-of-the-practice on CAV technologies and the potential impacts of CAVs on the intersection capacity. Deployment and market penetration rate prediction, traffic flow control strategy for CAVs, the intersection control strategy for CAVs, intersection capacity analysis methods (empirical-based and simulation-based methods), and intersection modeling scenarios and parameters of CAVs are also introduced and reviewed. These efforts could give a clear picture of the CAV technology and intersection capacity analysis methods in the existing capacity evaluation studies considering the impacts of different MPRs of CAVs at intersections.

After that, a hypothetical isolated four-way intersection is proposed as a basic scenario for the simulation. Meanwhile, one isolated intersection and two adjacent intersections in North Carolina are selected as field study scenarios. The layout, speed limits, peak-hour traffic volume, and pre-timed signal schemes of the intersection are all introduced. One isolated intersection and two adjacent intersections are selected as they could give representative results of the impact of CAVs on the intersection capacity. Also, two adjacent intersections are located between the downtown of Greensboro and the campus of the NCAT. Investigating these two adjacent intersections could give potential insights to Project 3 (which will be conducted by using CAVs to connect NCAT's campus to downtown Greensboro sites). This is the basic preparation for simulating intersection capacity with different MPRs of CAVs.

Micro-simulation methods and specific parameters for HDVs and CAVs are introduced. An initial pre-timed signal scheme for the hypothetical isolated intersection is calculated. Also, the intersection capacity is calculated by the empirical method to compare with the capacity obtained by the micro-simulation method. Specific scenarios for this isolated intersection and two field intersections in North Carolina are designed to investigate the potential impacts of CAV penetration rates on the intersection system.

Both the lane-level and intersection-level intersection capacity are analyzed in this research. In the lane-level capacity investigation, adjustment factors for saturation headway and saturation traffic flow rate for each lane group under different MPRs of CAVs are calculated. In the intersection-level capacity investigation, the maximum throughput of the intersection under different MPRs of CAVs is investigated. Also, the fitting curves and functions for the maximum throughput, total waiting time, total CO₂ emission, and total fuel consumption under different MPRs of CAVs are calibrated. Moreover, this research investigates the impacts of CAV penetration rates on the intersection with fixed traffic demands. It is noted that three variation tendencies of the total waiting time for the intersection system are observed under different traffic demand levels in three case studies. The results indicate that the benefits of CAV technologies at the intersection require a certain market penetration rate of CAVs and traffic demand level.

In summary, traffic engineers and planners are expected to be able to directly estimate the intersection capacity under mixed traffic environments by using the adjustment factors and functions calibrated in this research. The results and the analytical framework of this study could provide theoretical bases and fundamental guidance for transportation researchers and practitioners to better design, plan and operate intersection systems under CAV environments. Future research could also consider different platooning technologies of CAVs, investigate the safety impacts of mixed traffic, and provide specific control methods for CAV movements at intersections.

APPENDIX: C
GCN-CNVPS: Novel Method for Cooperative Neighboring Vehicle Positioning System Based on Graph Convolution Network

Appendix C GCN-CNVPS: Novel Method for Cooperative Neighboring Vehicle Positioning System Based on Graph Convolution Network

C.1 Introduction

Intelligent transportation systems (ITS) and autonomous vehicles (AV) enable several convenient applications and are expected to bring about new experiences with enhanced efficiency and safety to road users in the near future [317]. More specifically, ITS applications such as geographic information dissemination, traffic control, and the automatic positioning of accidents can be used to increase the efficiency of road users while traveling. By contrast, automatic collision avoidance systems in AVs can be employed to provide safety to road users. However, accurate localization is one of the most vital premises for the implementation of the aforementioned applications [188]. Although several localization methods, such as map matching, fingerprinting, and image/video localization, can be used to provide coordinate information of vehicles, the global positioning system (GPS) is still the most common choice for providing localization results to vehicles. There are two reasons for prohibiting the wide use of these methods. First, to apply these methods, expensive sensors, such as cameras and video recorders, should be installed in the target vehicle to provide the required information for matching or fingerprinting. To achieve accurate localization, acceptable sensors, which can be used to provide a high-resolution or high-quality output, are costly, hindering the widespread use of such methods. Second, to achieve an effective matching or fingerprinting, a database containing sufficient reference samples should be built in advance, prohibiting the wide use of these methods. Moreover, the need for a predefined database also limits the operation area for effective localization. As an alternative, GPS is the most commonly used localization system for vehicle applications, offering a cheap and easily accessible solution for global positioning [155].

Although GPS offers an easy and accessible way to conduct localization, the precision of GPS still has room for further improvement in providing accurate localization. To be more specific, GPS suffers from the influence of several factors (e.g., receiver noise and a multipath effect) such that the received GPS coordinates have large errors with the actual coordinates of the vehicle, thereby posing a threat to the safety of the AV or the precision of ITS applications. To solve this drawback by working on the GPS error refinement, vehicular ad-hoc networks (VANETs) [85] have recently been introduced to the automotive research community where vehicles can communicate with each other to improve their location awareness [127, 188, 218, 265]. By integrating vehicle-to-vehicle (V2V) communication, an effective “cooperative driving” network can be established to share information for GPS refinement usage. To be more specific, several studies have already focused on incorporating GPS with auxiliary information (e.g., ranging measurement and reference points) through optimization-based algorithms to enhance the system performance [188]. In [127], the authors proposed a direction of arrival (DOA)-based cooperative localization method, incorporating GPS with radar to improve the localization. Furthermore, because the information coming from each sensor has its own limitations, the concept of data fusion has been introduced into the GPS refinement to refine the GPS results based on the information acquired from multiple sensors. In addition, in [218], the authors proposed a cooperative neighboring vehicle positioning system (CNVPS), incorporating GPS with various sensors using the weighted average to improve the localization. However, the approach in [218] only employs a linear function for the application of a sensor data fusion for GPS refinement, thereby leaving room for further performance improvements. Although more powerful algorithms should be developed to improve the performance of existing CNVPS algorithms, the design of advanced optimization-based CNVPS algorithms is not trivial. First, the design is highly dependent on the precise domain knowledge of different information sources (i.e., the error distribution of extra sensors), which may not be easily available under real scenarios. Moreover, the optimization problem should be redesigned if different types of sensors are employed. Second, to achieve accurate results, multiple iterations or complex matrix operations are often employed in the optimization process. Finally, although the problem of interest can be considered time-series data (i.e., multi-time-slot data), existing optimization-based methods only focus on the scenario of a single time-slot data fusion. As a result, the modeling of an optimization problem for extracting the correlation in multiple time-slot data and further improving the performance remains an open problem.

Differing from existing optimization-based algorithms, our idea is to develop CNVPS algorithms based on a deep learning (DL) algorithm owing to such advantages as a low complexity, high performance, and design flexibility. Specifically, given a sufficient training dataset, even without a precise mathematical system model, the DL model can be used to construct a nonlinear function and automatically solve the optimization problem of interest. Moreover, during the online testing stage, only simple matrix operations are executed when generating

GPS refinement results, matching the computational limitations of on-board vehicle units. Furthermore, the DL model can extract hidden features (i.e., correlation of a multiple time-slot scenario) to further improve the GPS refinement results, making it almost impossible for optimization-based algorithms to do the same. Based on the aforementioned motivations, we decided to focus on the development of DL-based CNVPS GPS refinement algorithms. As a result, we can not only fully fuse various sensors but also integrate multiple time-slot data by introducing flexible characteristics of DL algorithms. For a single time-slot GPS refinement, we propose a multi-layer perceptron-cooperative neighboring vehicle positioning system (MLP-CNVPS) to achieve DL-based GPS refinement. Considering a multiple time-slot GPS refinement, we propose a long short-term memory-cooperative neighboring vehicle positioning system (LSTM-CNVPS) for obtaining superior results by considering the temporal correlation in multiple time-slot data. Moreover, a graph convolution network-cooperative neighboring vehicle positioning system (GCN-CNVPS) was further developed to better utilize both temporal and spatial correlations and achieve an efficient GPS refinement, leading to an even better performance compared to the aforementioned DL-based CNVPS algorithms. Simulation results show that the performance of the proposed DL-based localization approach is better than that of existing optimization-based localization algorithms by improving the GPS error mean from 4 – 20 m to 2 – 4 m. This improvement is comparable to the current V2I localization performance [109], thus verifying the contribution of this study. Moreover, as [61] reported, an error mean of approximately 6 – 8 m is sufficient for most vehicular applications using V2V ranging, and our study is a strong candidate to be implemented in V2V applications with the advantages of low-cost hardware, a fast and simple method, and an accurate and stable performance.

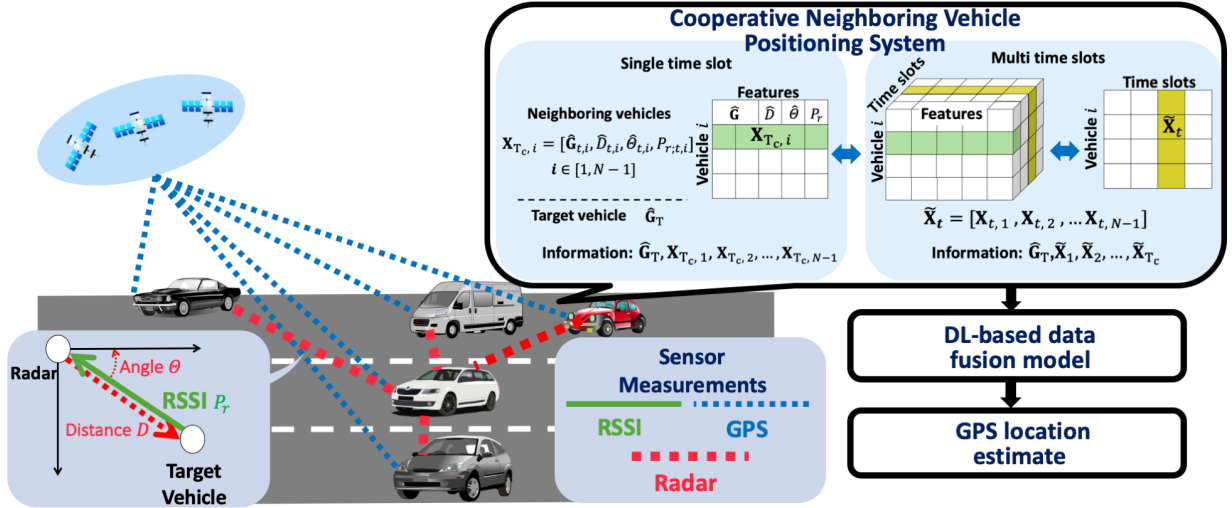


Figure 92. The considered scenario of cooperative vehicle localization through V2V. V2V communication is used to transmit additional information acquired from on-board sensors for the use of GPS refinement. The information is arranged in a specific format and fed into the DL-based CNVPS algorithm, generating GPS-refined results.

The remainder of this paper is organized as follows. In Section C.2, the system model and sensor configurations are as described below. Section C.3 illustrates the proposed method in detail, including the framework of the deep learning-based localization approach and the operations in both the online and offline stages. The simulation results are presented in Section C.4, followed by some concluding remarks in Section C.5.

C.2 System Setup and Problem Formulation

C.2.1 System Setup: As shown in Fig. 92, a cooperative group consisting of N vehicles is considered to enable a CNVPS-aided localization refinement [218]. With the support of vehicle-to-vehicle (V2V) communications, a target vehicle can use extra information from the GPS localization results of neighboring vehicles in the group and sensors in the vehicle to refine the GPS localization result. Specifically, GPS installed in each vehicle is used to estimate the vehicle coordinates. Moreover, commonly used omnidirectional radar is also employed in each vehicle to measure the relative distance and angle of the surrounding vehicles. We further assume that these measurements can be matched to the right surrounding vehicle owing to the matching ability of the sensors and GPS [218]. We also assume that each vehicle in the group can communicate with neighboring vehicles through V2V, which is used as a setting in

related studies [127, 188, 218, 265]. To explain this, the basic safety message (BSM) [7] and the optional part of the BSM, which is supported by both dedicated short-range communication [218] [141] and cellular vehicle-to-everything standards [325], can satisfy our need to exchange information between vehicles in a group. As a whole, in each BSM frame (i.e., time slot), each vehicle can acquire the GPS coordinate results of all surrounding vehicles (from GPSs and V2V exchanges), the relative distance and angle to other vehicles (from on-board omnidirectional radar), and the received signal strength indication (RSSI) of other vehicles (from V2V exchange) for achieving CNVPS-aided localization refinement for a refined GPS localization result.

C.2.2 Sensor Configuration: In this section, we introduce the sensor configurations used in this study, including GPS, radar, and RSSI.

C.2.2.1 GPS: In this study, it is assumed that the GPS error follows a Gaussian distribution, as there are several independent sources, such as satellite clock bias, atmospheric delay, code acquisition noise, and multipath effect, contributing to the GPS error in practice [78, 243, 341]. In each case, the relationship between the GPS localization result $\hat{\mathbf{G}} \in \mathbb{R}^2$ and the real position $\mathbf{G} \in \mathbb{R}^2$ of a vehicle can be expressed as follows:

$$\hat{\mathbf{G}} = \mathbf{G} + \mathbf{n}, \quad (\text{C.1})$$

where $\mathbf{n} = [\text{Re}\{a|\mathbf{e}^j\}, \text{Im}\{a|\mathbf{e}^j\}]^T$ denotes the error term with $a \sim N(\mu, \sigma^2)$ and $\theta \sim u(0, 2\pi)$. According to existing literature [153], because the levels of the multipath effect are site-dependent, the statistical properties of the Gaussian distribution should be set differently to reflect the GPS error in different environments. In this study, we simulated three different environments to validate the robustness of different CNVPS-aided refinement algorithms. Specifically, in this study, three environments, including **free space** (e.g., highway environment), **suburban**, and **urban** scenarios, were considered and set as $N(4.7, 4.84)$, $N(14.8, 49)$, and $N(20.5, 72.25)$, respectively, [188] to reflect the GPS estimation behavior.

C.2.2.2 Radars: In this study, radar is used to provide the relative distance and angle of the surrounding vehicles as an information source for GPS refinement. To simulate the radar measurements, the relationship between the radar distance measurement $\hat{D} \in \mathbb{R}$ and the real distance $D \in \mathbb{R}$ of a vehicle can be expressed as follows:

$$\hat{D} = D + \check{n}_D, \quad (\text{C.2})$$

where $\check{n}_D \sim u(-0.025D, 0.025D)$ describes the longitudinal uncertainty of the measurement related to the true distance. Note that the uncertainty increases with the real distance, satisfying the realistic radar measurement behavior. Moreover, the relationship between the angle measurement $\hat{\Theta} \in R$ and the real angle $\Theta \in R$ of a vehicle can be expressed as follows:

$$\hat{\Theta} = \Theta + \check{n}_\Theta, \quad (\text{C.3})$$

where $\check{n}_\Theta \sim u(-0.5, 0.5)$ describes the lateral uncertainty of the radar measurement with an angular error of 0.5° according to [68].

C.2.2.3 RSSI: Despite the radar measurements, because we adopt BSM to serve V2V communication, the RSSI information can also be acquired in each frame of the BSM to provide another distance measurement for the GPS refinement [17, 263]. To model the RSSI measurements, the practical path loss can be described as a log-normally distributed random variable with a distance-dependent location parameter [60, 200]. That is,

$$P_r(d) = P_0(d_0) - 10n_p \log_{10}\left(\frac{d}{d_0}\right) + \tilde{n}, \quad (\text{C.4})$$

where $P_r(d)$ denotes the received signal strength measured in decibel milliwatts (dBm) at the transmitter-receiver distance d (in meters), $P_0(d_0)$ denotes the reference power (in dBm) at a reference distance d_0 (in meters), n_p is the channel path loss exponent, and $\tilde{n}$ is the effect of channel fading. To conduct the simulation in this study, we set the aforementioned parameters as $P_0(d_0) = -34$, $n_p = 2.1$, and $\tilde{n} \sim N(0, 5.5^2)$.

C.2.3 Problem Statement: The GPS refinement problem can be considered as a method for improving the GPS localization based on the extra aforementioned information. Hence, the goal of this study is to design a function that takes extra information and the original GPS estimations as input and returns the refined GPS estimation result, minimizing the difference between the predicted result and the real position of the target vehicle by means of

data fusion. Specifically, as shown in Fig. 1, in each vehicle in the group, through a V2V information exchange, the extra information $\mathbf{X}_{t,i}$ is available in each vehicle i at time slot t for the refinement of the GPS localization result. Based on the aforementioned sensor configurations, the extra information can be further expressed as $\mathbf{X}_{t,i} = [\hat{\mathbf{G}}_{t,i}, \hat{\mathbf{D}}_{t,i}, \hat{\mathbf{A}}_{t,i}, \mathbf{P}_{r,t,i}] \in \mathbf{R}^5$, which contains the GPS, relative distance to the target vehicle, the relative angle to the target vehicle, and the RSSI. Hence, for a target vehicle in the group with GPS measurements $\hat{\mathbf{G}}_T$, the problem we address can be expressed as a function design problem. That is,

$$f^* = \arg \min_f \|f(\hat{\mathbf{G}}_T, \mathbf{X}_{T_c,1}, \mathbf{X}_{T_c,2}, \dots, \mathbf{X}_{T_c,N-1}) - \mathbf{G}_T\|^2, \quad (\text{C.5})$$

where $\mathbf{X}_{T_c,1}, \mathbf{X}_{T_c,2}, \dots, \mathbf{X}_{T_c,N-1}$ are the extra information from other $N-1$ vehicles in the group at the current time slot T_c . Note that all algorithms in the previous studies [188] [127], [78, 218, 243] can also be regarded as designing the prediction function through the optimization process. Furthermore, considering that a cooperative group usually exists for several BSM transmission periods (i.e., multiple time slots), for multi-time-slot scenarios, although we can deal with different time slots independently using single time-slot CNVPS solutions, we try to further improve the GPS localization result by using the correlation between multi-time-slot measurements. In light of this, we first consider the GPS refinement problem under the multiple time-slot scenario in this study. In particular, the multiple time-slot problem we considered can be expressed as

$$f^* = \arg \min_f \|f(\hat{\mathbf{G}}_T, \tilde{\mathbf{X}}_1, \tilde{\mathbf{X}}_2, \dots, \tilde{\mathbf{X}}_{T_c}) - \mathbf{G}_T\|^2, \quad (\text{C.6})$$

where $\tilde{\mathbf{X}}_1, \tilde{\mathbf{X}}_2, \dots, \tilde{\mathbf{X}}_{T_c}$ are the features of the previous time slots and can be further expressed as $\tilde{\mathbf{X}}_t = [\mathbf{X}_{t,1}, \mathbf{X}_{t,2}, \dots, \mathbf{X}_{t,N-1}]$. Note that Eq. (5) can be regarded as a special case of Eq. (6) when only one time-slot information is provided for GPS refinement.

C.3 Development of DL-based Localization Algorithms

C.3.1 Overview: Our idea is to develop CNVPS algorithms based on DL algorithms owing to their low complexity, high performance, and design flexibility. More specifically, for a single time-slot GPS refinement, we propose a multi-layer perceptron-cooperative neighboring vehicle positioning system (MLP-CNVPS) to achieve a DL-based GPS refinement. For a multiple time-slot GPS refinement, to obtain superior results by considering the temporal correlation in multi-time-slot data, we propose a long short-term memory-cooperative neighboring vehicle positioning system (LSTM-CNVPS). Moreover, a graph convolution network-cooperative neighboring vehicle positioning system (GCN-CNVPS) was further developed to better utilize both temporal and spatial correlations for achieving an efficient GPS refinement, leading to an even better performance compared to the aforementioned DL-based CNVPS algorithms. In the remainder of this section, the motivations and details of the DL-based CNVPS GPS refinement algorithm with different structures are first introduced, and followed by the training specifics at the end of this section.

C.3.2 Architecture of the Proposed MLP-CNVPS: As shown in Fig. 2 (a), we propose MLP-CNVPS based on a conventional MLP DL model. Under the multiple time-slots scenario, all extra information and original GPS measurements of the target vehicle will be directly fed into the MLP-CNVPS without preprocessing. As a result, the input layer of MLP-CNVPS can be expressed as a vector of size $1 \times ((5 \times (N-1) + 2) \times T)$, where T is the number of time slots, according to the considered system model (i.e., the extra information from $N-1$ vehicles from the same cooperative group and the GPS measurements of the target vehicle itself). Following the input layer, we constructed four fully connected layers as hidden layers to process the input data. The neurons in each layer were set to 256, 128, 64, and 32, respectively. Behind each layer, the parametric rectified linear unit (PReLU) [120] is employed as the activation function to provide nonlinearity. Then, the output of the last hidden layer is fed into the output layer with two neurons, generating the refined localization of the target vehicle.

As a mathematical expression, the MLP-CNVPS model for multiple time-slot scenarios can be described as follows:

$$f_{\text{MLP-CNVPS}}(\hat{\mathbf{G}}_T, \tilde{\mathbf{X}}_1, \tilde{\mathbf{X}}_2, \dots, \tilde{\mathbf{X}}_{T_c}; \mathbf{\Theta}_{\text{MLP}}) = \Gamma(W_{\text{out}} \dots \Gamma(W_2 \Gamma(W_1 X_{\text{MLP}} + b_1) + b_2) + \dots + b_{\text{out}}), \quad (\text{C.7})$$

where W_i and b_i represent the weights and bias of the i th layer, respectively, Γ function is the employed PReLU

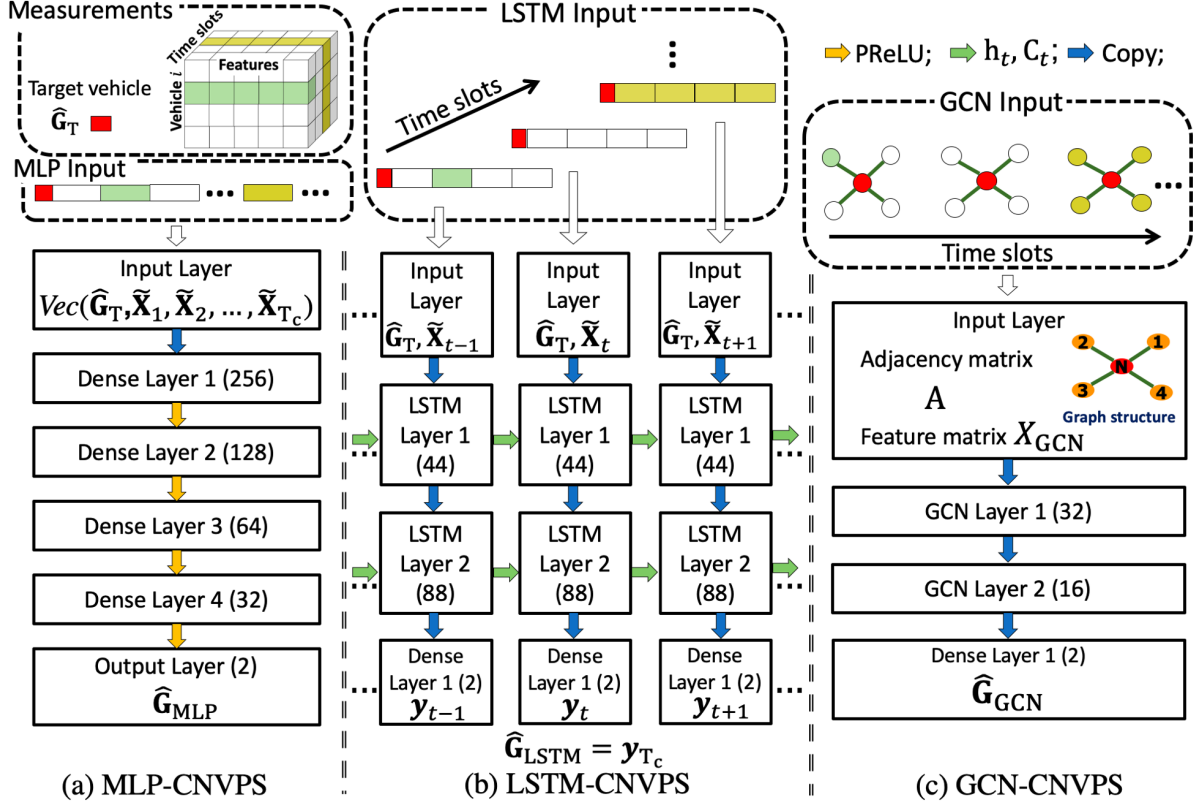


Figure 93. Illustration of the proposed model structures under a multiple time-slot condition. (a) MLP-CNVPS: All input data from multiple time slots are fed into the model directly without further pre-processing. (b) LSTM-CNVPS: Input data from multiple time slots are separated and fed into the model in different time slots to emphasize the temporal correlation. (c) GCN-CNVPS: Using the special kernel design of a GCN, the adjacency matrix is used to describe the spatial correlation of input data under the graph structure, and to achieve a superior performance, the temporal and spatial correlation in the input feature matrix will be simultaneously emphasized.

activation function. In addition, $\Theta_{MLP} = \{\{W_i, b_i\}_{i=1}^4, W_{out}, b_{out}\}$ represents all trainable parameters, and $X_{MLP} = Vec(\hat{G}_T, \tilde{X}_1, \tilde{X}_2, \dots, \tilde{X}_{T_c})$, where $Vec(\cdot)$ is a vectorized operation. Note that the MLP-CNVPS under a single time-slot scenario can be considered as a special case of Eg. (7) when $T_c = 1$. With the aforementioned DL model architecture, MLP-CNVPS, can be used to construct a nonlinear function and extract hidden information in the given input to refine the GPS estimation results automatically. The simulation results confirm that MLP-CNVPS outperforms the existing CNVPS solutions.

C.3.3 Architecture of the Proposed LSTM-CNVPS: Although MLP-CNVPS can extract hidden information in multiple time-slot measurements and provide an improved GPS refinement, the performance achieved can be further improved by further utilizing the correlation of multi-time-slot measurements along the temporal axis. For the considered problem, multiple time-slot measurements actually belong to the time-series data format. However, it should be noted that all features from different time slots are fed into MLP-CNVPS simultaneously, failing to emphasize the correlation of multiple time-slot measurements in the temporal axis. As an alternative, we further propose LSTM-CNVPS to better utilize a temporal correlation in multiple time-slot measurements. More specifically, the proposed LSTM-CNVPS, as shown in Fig. 2(b), is based on LSTM to leverage its ability to extract hidden information in multiple time-slot measurements.

In time slot t , the operation of the LSTM-CNVPS can be expressed as follows:

$$\begin{aligned}
f_t &= \sigma(W_f^l[h_{t-1}, X_{\text{LSTM},t}] + b_f^l) \\
i_t &= \sigma(W_i^l[h_{t-1}, X_{\text{LSTM},t}] + b_i^l) \\
o_t &= \sigma(W_o^l[h_{t-1}, X_{\text{LSTM},t}] + b_o^l) \\
\tilde{C}_t &= \tanh(W_c^l[h_{t-1}, X_{\text{LSTM},t}] + b_c^l) \\
C_t &= f_t \odot C_{t-1} + i_t \odot \tilde{C}_t \\
h_t &= o_t \odot \tanh(C_t)
\end{aligned} \tag{C.8}$$

where h_t is the state vector, and $X_{\text{LSTM},t} = \text{Vec}(\hat{\mathbf{G}}_T, \tilde{\mathbf{X}}_t)$ of time slot t . In addition, $W_f^l, W_i^l, W_o^l, W_c^l$, and $b_f^l, b_i^l, b_o^l, b_c^l$ are the weights and biases of the l th layer. Moreover, $\sigma(x) = \frac{1}{1+e^{-x}}$ is the sigmoid function, and $\tanh(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}}$ is the hyperbolic tangent function. The $\odot$ operation represents an element-wise multiplication. It is noteworthy that in every time slot, a state vector h will be generated and considered as an input in the next time slot. By doing so, important information from the measurements of the previous time slot will be extracted and kept in this state vector, thereby affecting the operation of LSTM-CNVPS in the next time slot and emphasizing and better utilizing the correlation in the temporal axis compared to MLP-CNVPS. For the model structure, we constructed an LSTM-CNVPS with two LSTM layers, and the LSTM units of each layer were 44 and 88, respectively. The output is fed into a fully connected layer, which contains two neurons and is regarded as a refined location estimation. The full LSTM-CNVPS model can be described as follows:

$$f_{\text{LSTM-CNVPS}}(\hat{\mathbf{G}}_T, \tilde{\mathbf{X}}_1, \tilde{\mathbf{X}}_2, \dots, \tilde{\mathbf{X}}_{T_c}; \Theta_{\text{LSTM}}). \tag{C.9}$$

where Θ_{LSTM} is the set of all trainable weights and biases, and is further expressed as

$$\Theta_{\text{LSTM}} = \{\{W_f^l, W_i^l, W_o^l, W_c^l, b_f^l, b_i^l, b_o^l, b_c^l\}_{l=1}^2, W_{out}, b_{out}\}. \tag{C.10}$$

Finally, it is worth noting that when we employ LSTM-CNVPS to solve the GPS refinement problem in a single time-slot scenario, because there is only one time slot in (8), the special mechanism of LSTM used to extract the temporal correlation will no longer exist, and the behavior of LSTM-CNVPS is retrograde to that of MLP-CNVPS.

C.3.4 Architecture of the Proposed GCN-CNVPS: Although LSTM-CNVPS can better utilize a temporal correlation to improve the performance of MLP-CNVPS, neither MLP-CNVPS nor LSTM-CNVPS consider the spatial correlation of neighboring vehicles. To explain, the extra information provided by different neighboring vehicles should have different weights or levels of confidence considering the relative distance in an adaptive manner, MLP-CNVPS and LSTM-CNVPS cannot support a delicate design for handling this aspect. To further improve the performance of vehicle localization, we propose GCN-CNVPS to simultaneously consider both temporal and spatial correlations. To do so, if the input data belongs to Euclidean space (i.e., image data), a convolutional neural network (CNN) can satisfy the need to consider both temporal and spatial correlations simultaneously based on its special kernel design and consequent convolution operations. However, the input data of the problem considered belongs to a graph representation, limiting the usage of the CNN model. As an alternative, Fig. 2(c) presents the architecture of the proposed GCN-CNVPS. The input for the GCN-CNVPS is represented by an adjacency matrix A and a feature matrix X_{GCN} . Specifically, the adjacency matrix is used to describe the graph structure of interest, allowing the GCN to utilize the spatial correlation in the considered graph structure. We describe this structure to reflect the fact that the target vehicle is able to communicate with the neighboring $N-1$ vehicles, despite these $N-1$ vehicles having no connections with each other. The resulting adjacency matrix of size $N \times N$ can be defined as follows:

$$A = \begin{bmatrix} 0 & 0 & \dots & 0 & 1 \\ 0 & 0 & \dots & 0 & 1 \\ \vdots & \vdots & \ddots & \vdots & \vdots \\ 0 & 0 & \dots & 0 & 1 \\ 1 & 1 & \dots & 1 & 0 \end{bmatrix}. \tag{C.11}$$

However, notice that directly employing adjacency matrix A into GCN-CNVPS causes numerical problems (a gradient explosion and vanishing problem) [353] during the training process, failing to lead to the convergence of optimal

weightings. As a result, a normalized adjacency matrix is adopted to prevent the aforementioned issue. In particular, $\hat{A} = \tilde{D}^{-\frac{1}{2}}(A + I_N)\tilde{D}^{-\frac{1}{2}}$ is a normalized adjacency matrix with added-self connections, where I_N is the identity matrix, $\tilde{D} = D + I_N$ is the degree matrix, and $D = \text{diag}(\sum_j A_{ij}) \in \mathbb{R}^{N \times N}$. The first $\tilde{D}^{-\frac{1}{2}}$ represents the normalization for each row, and the second represents that for each column. By using the normalized adjacency matrix, the numerical problem during the GCN model training process can be solved. For the model input, the feature matrix X_{GCN} can be represented as a matrix with N rows and $((3 \times (N-1) + 2) \times T)$ columns, representing N vehicles and $(3 \times (N-1) + 2) \times T$ measurements for T time slots, respectively. To utilize the spatial correlation effectively, the information of each surrounding vehicle should be assigned and placed carefully to be processed separately. Specifically, for the i th row ($i \in [1, N-1]$ for the neighboring vehicles), the measurements are $[\hat{\mathbf{G}}_{t,i}, 0, \dots, \hat{D}_{t,i}, 0, \dots, \hat{\Theta}_{t,i}, 0, \dots, P_{r,t,i}] \in \mathbb{R}^{(3 \times (N-1) + 2)}$. That is, each neighboring vehicle only acquires the observations of itself and has no information about other vehicles, letting the corresponding values to be set to 0. By contrast, for the N th row (the target vehicle), the measurements of time slot t can be expressed as $[\hat{\mathbf{G}}_{t,N}, \hat{D}_{t,1}, \dots, \hat{D}_{t,N-1}, \hat{\Theta}_{t,1}, \dots, \hat{\Theta}_{t,N-1}, P_{r,t,1}, \dots, P_{r,t,N-1}] \in \mathbb{R}^{(3 \times (N-1) + 2)}$. To explain this, the target vehicle possesses its own GPS measurement as well as radar observations and RSSI obtained from neighboring $N-1$ vehicles through V2V communications.

Note that the dimensions of the measurements are slightly different from the previous to separate the acquired information of each vehicle by arranging the measurements in different rows. However, the overall amount of information remains the same.

Finally, for the structure of GCN-CNVPS, to exploit the spatial dependence in the input features, we employed two GCN layers [107] [43], with the number of neurons in each layer being 32 and 16, respectively, in GCN-CNVPS. Specifically, the convolution function of the GCN layer can be expressed as follows:

$$f_{\text{conv}}(X_{\text{GCN}}; \hat{A}) = \Gamma(\hat{A}X_{\text{GCN}}W + b). \quad (\text{C.12})$$

The Γ function is the employed PReLU activation function. Here, W and b represent the trainable weight matrix and bias matrix, respectively. In (C.12), $\hat{A}X_{\text{GCN}}W$ aggregates all features of neighboring nodes with trainable weights for each node. According to [69, 111, 149], the operation is analogous to the function of the convolutional kernels in convolutional neural networks (CNNs) and is therefore capable of extracting spatial characteristics in a graph. The output of the last GCN layer was flattened and fed into a fully connected layer. The number of neurons in each layer was 2. The complete operations of GCN-CNVPS can be formulated as follows:

$$\begin{aligned} f_{\text{GCN-CNVPS}}(X_{\text{GCN}}; \hat{A}; \Theta_{\text{GCN}}) &= f_{\text{out}}(f_{\text{conv2}}(f_{\text{conv1}}(X_{\text{GCN}}; \hat{A}), \hat{A})) \\ &= W_{\text{out}}(\Gamma(\hat{A}\Gamma(\hat{A}X_{\text{GCN}}W_1 + b_1)W_2 + b_2)) + b_{\text{out}} \end{aligned} \quad (\text{C.13})$$

Θ_{GCN} is the set of all trainable weights and biases, which can be represented as

$$\Theta_{\text{GCN}} = \{W_1, W_2, b_1, b_2, W_{\text{out}}, b_{\text{out}}\}. \quad (\text{C.14})$$

C.3.5 Training Method: To train the aforementioned DL-based models, supervised learning algorithms were adopted, and the mean square error was employed as the loss function as follows:

$$L(\Theta) = \frac{1}{D} \sum_{i=1}^D (\varphi_i - f(X_i; \Theta))^2, \quad (\text{C.15})$$

where $f(X_i; \Theta)$ is the DL-based model that estimates the result corresponding to a sample X_i with trainable weightings Θ , φ_i is the true localization, and D is the total number of samples in the training dataset. Adam [148], a popular gradient descent-based optimizer, was employed to iteratively reduce the loss of each epoch through a backpropagation algorithm during the training process. For MLP-CNVPS, the initial learning rate was set to 0.00001, and the batch size was set to 128. After 1000 epochs, the trained weightings of MLP-CNVPS were recorded, and the offline training process was completed. For LSTM-CNVPS, we set the initial learning rate to 0.00005 and the batch size to 128. After 1000 epochs, the trained weights of the LSTM-CNVPS were recorded, and the LSTM training was completed. For GCN-CNVPS, we set the initial learning rate to 0.0001 and the batch size to 128. After 750 epochs, the trained weights and bias of the GCN-CNVPS were recorded, and the GCN training was completed. Once the offline training process is completed, during the online testing process, the trained DL model can be used to provide vehicle localization estimation results without any further operations.

C.4 Simulation Results and Discussion

In this section, three proposed DL-based CNVPS algorithms, MLP-CNVPS, LSTM-CNVPS, and GCN-CNVPS, are evaluated and compared to three existing optimization-based CNVPS algorithms. More specifically, the existing optimization-based CNVPS algorithms, centroid location (CL) algorithm [21], DOA-based location algorithm [127], and optimization-based CNVPS algorithm [218] are implemented in this study as benchmarks. Without the assistance of extra sensors, the CL algorithm simply averages the GPS coordinates of neighboring vehicles to estimate the location of the target vehicle. Thus, the variance of the GPS estimations can be reduced. With the assistance of radar, the DOA-based locating algorithm employs the direction of arrival information of neighboring vehicles to estimate the position of the target vehicle. However, this algorithm cannot exploit additional sensors to further improve the performance. As in the previous study, CNVPS successfully utilizes various sensors to estimate the coordinates of the target vehicle and conducts weighted average localization considering prior knowledge in terms of the standard deviation of each extra sensor. However, because CNVPS only employs a linear function to exploit the information from extra sensors, the achieved performance is limited. Moreover, because the weightings of different sensors are pre-defined according to the statistics of the sensors and remain fixed, the CNVPS cannot adjust the weightings adaptively according to different inputs to achieve better performance. Furthermore, CNVPS also fails to be employed in multiple time-slot scenarios to further improve the performance. In contrast to existing algorithms, DL-based algorithms provide a way to design an adaptive nonlinear function to better utilize the information from extra sensors by extracting temporal and spatial correlations. Moreover, multiple time-slot scenarios can be considered and supported to provide a superior performance compared to a single time-slot scenario. In this section, we first introduce the process of data generation and then compare different algorithms in different scenarios to validate the superiority of DL-based CNVPS algorithms.

C.4.1 Data Generation: To obtain the dataset for model training and testing, we first generate the coordinates of the target vehicle $\mathbf{G}_T$ and then generate neighboring $N - 1$ vehicle coordinates $\{\mathbf{G}_i\}_{i=1}^{N-1}$ with a distance constraint $\|\mathbf{G}_T - \mathbf{G}_i\|^2 < 10$ (unit: meters). Subsequently, we can obtain measurements according to the sensor configurations mentioned in Section C.2. For the generation of multiple time-slot measurements, we specify the vehicle mobility by setting the horizontal velocity V_h and vertical velocity V_v for each vehicle. Moreover, we defined two driving modes, the **straight-through mode** and the **lane change mode**, to set the driver behavior. The vehicle velocities of the former are set as $V_h = 0$ and $V_v \sim \mathcal{U}(10, 15)$ m/s, the latter of which are set as $V_h \sim \mathcal{N}(0, 1.5^2)$ and $V_v \sim \mathcal{U}(10, 15)$ m/s. Based on the aforementioned settings, we set the number of samples for training, validation, and testing datasets to 100000 for each of these three scenarios under different driving modes. We then compute the resulting average mean and standard deviation of the different algorithms to report the error statistics.

C.4.2 Performance Analysis with Single Time-Slot Measurements: In this section, we simulate and discuss the behavior of different CNVPS algorithms in three practical scenarios: **free space**, **suburban**, and **urban**, under a single time-slot measurement condition. Fig. 3 shows the achieved mean and standard deviation of the estimation error for different algorithms under three scenarios with a cooperative group size equal to 5. Although optimization-based algorithms can improve the GPS estimation error, DL-based algorithms can further improve the GPS measurements by showing a lower achieved mean and standard deviation for all scenarios. Specifically, regardless of the severity of the original GPS estimation error, DL-based CNVPS algorithms can refine the GPS estimations and provide a certain level of improvement. It is also worth noting that GCN-CNVPS slightly outperforms MLP-CNVPS because the spatial correlation is emphasized and better utilized through the special mechanism of GCN operations.

C.4.3 Performance Analysis with Multiple Time-Slot Measurements: In this section, we discuss the performance of different algorithms under three scenarios with multiple time-slot measurement conditions. Because none of the existing optimization-based algorithms can be extended to multi-time-slot conditions, in this section, we describe the application a single time-slot CNVPS algorithm, which showed the best results among the optimization-based algorithms in the previous simulation, in each time slot instead as a benchmark. Fig. 4 illustrates the error statistics for different algorithms under the three scenarios when the driving mode is set as the straight-through mode in a cooperative group containing five vehicles. Compared to CNVPS, which fails to utilize information from multiple time-slot measurements to further improve the performance, as the number of time slots increases, all three DL-based CNVPS algorithms can gain from the extra information and achieve a better performance compared to single time-slot measurement conditions. More specifically, LSTM-CNVPS outperforms MLP-CNVPS because of the special mechanism for emphasizing a temporal correlation. Furthermore, GCN-CNVPS can offer a better performance than LSTM-CNVPS because temporal and spatial correlations are both considered through the convolution operations

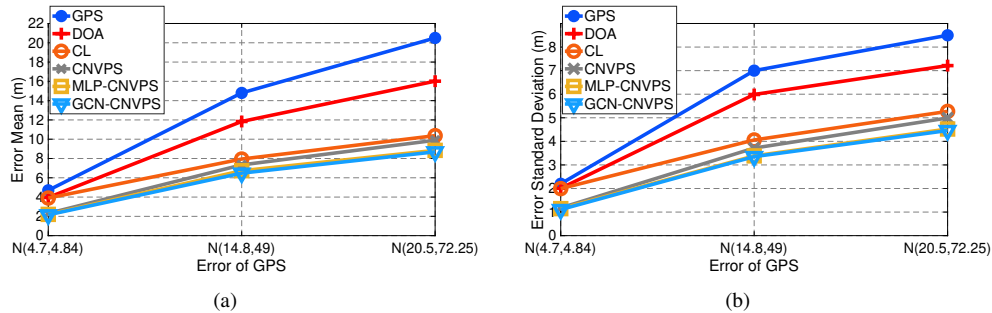


Figure 94. (a) Error mean versus scenarios and (b) error standard deviation versus scenario performance with $N = 5$ and $T_c = 1$.

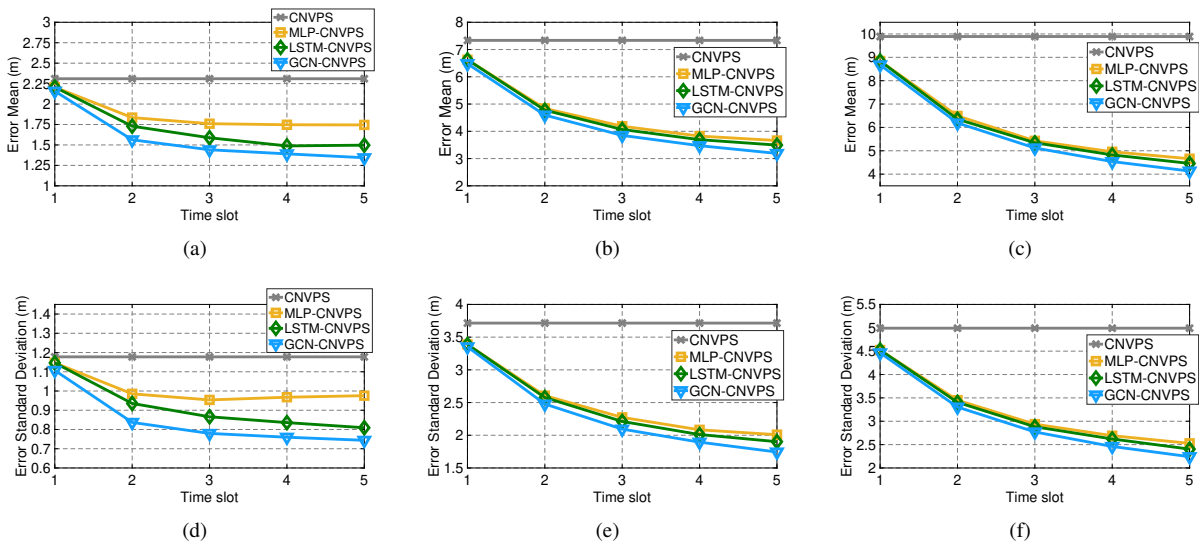


Figure 95. Error mean versus time slot performance under (a) free space, (b) suburban, and (c) urban scenarios in straight-through mode with $N = 5$. (d)–(f) Plots of the same for the standard deviation of the error.

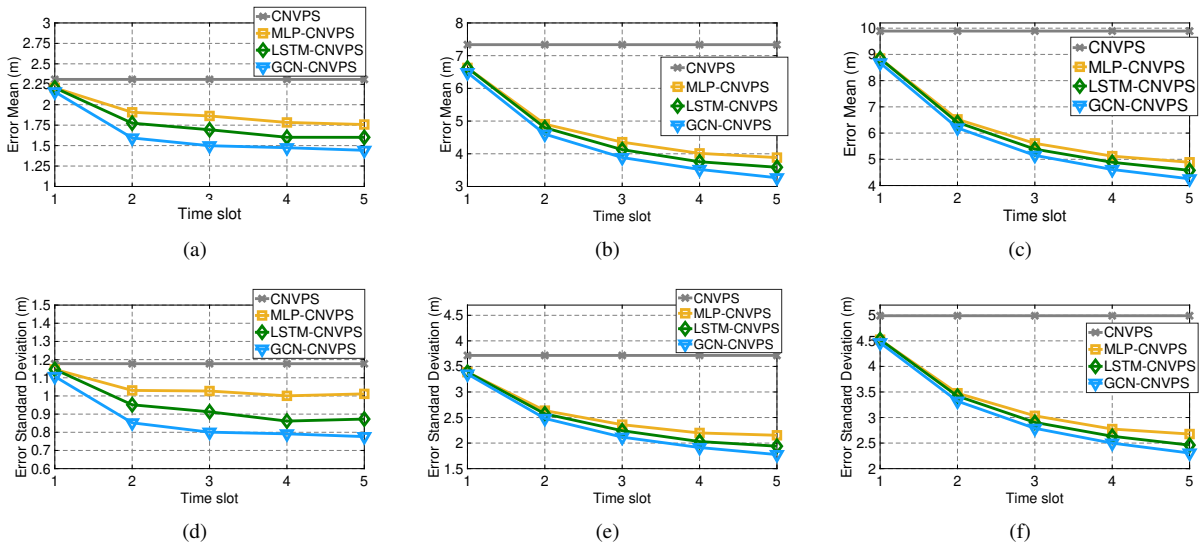


Figure 96. Error mean versus time slot performance under (a) free space, (b) suburban, and (c) urban scenarios in lane change mode with $N = 5$. (d)–(f) Plots of the same for the standard deviation of the error.

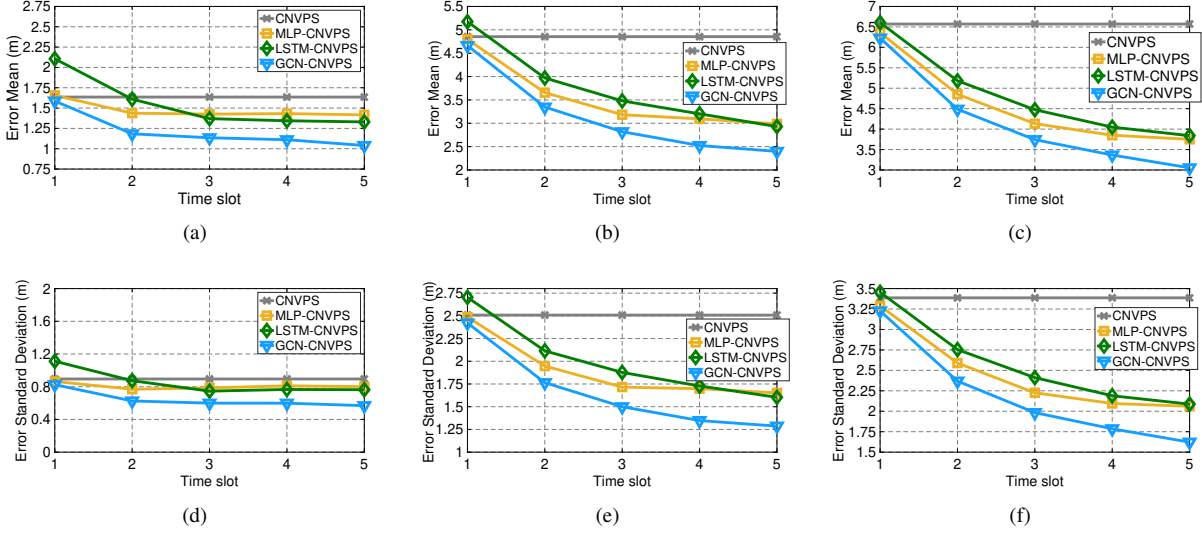


Figure 97. Error mean versus time slot performance under (a) free space, (b) suburban, and (c) urban scenarios in straight-through mode with $N = 10$. (d)–(f) Plots of the same for the standard deviation of the error.

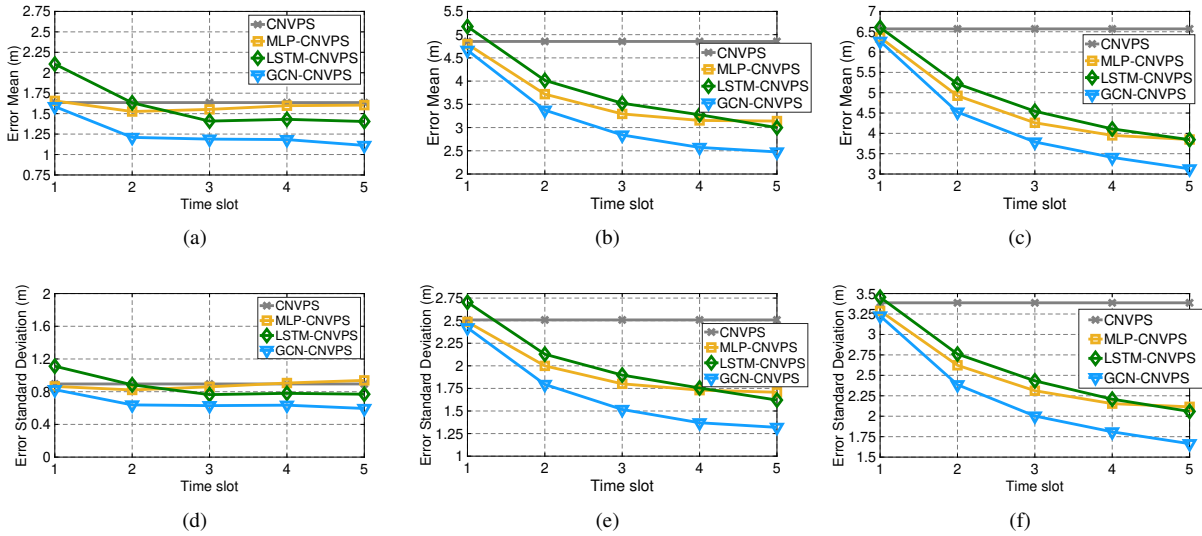


Figure 98. Error mean versus time slot performance under (a) free space, (b) suburban, and (c) urban scenarios in lane change mode with $N = 10$. (d)–(f) Plots of the same for the standard deviation of the error.

of the GCN model. However, we can also note that the improvement of the urban case is more compelling because the GPS error in this scenario has more room for improvement. However, even under the free-space scenario, DL-based CNVPS algorithms can still be used to improve the original GPS estimation results. Fig. 5 shows the error statistics for different algorithms under the same three scenarios when the driving mode is set as the lane-change mode in a cooperative group containing five vehicles. Nevertheless, we can observe the same behaviors of the three algorithms by showing impressive improvements over the results of the CNVPS algorithm. Note that straight-through mode is easier than lane-change mode because of the relatively fewer variations in directions and relatively higher correlation of locations at different time slots. Hence, we found that all methods perform worse than the straight-through mode. However, among them, GCN-CNVPS always achieved the best performance in both modes. These results suggest that GCN-CNVPS enhances the performance of GPS by extracting temporal and spatial relationships from historical measurements, confirming our motivation toward the design of GCN-CNVPS.

C.4.4 Scalability of Proposed Algorithms: In this section, we further verify the scalability of the proposed algorithms by extending our algorithms to a vehicular scenario that consisting of ten cars. Figs. 6 and 7 present the

error statistics for different algorithms in the three scenarios under different driving modes in a cooperative group containing ten vehicles. With additional information provided by increasing the number of surrounding vehicles, the performance of all DL-based CNVPS algorithms improved compared to the previous simulations. However, we also noted that because MLP-CNVPS and LSTM-CNVPS cannot utilize a spatial correlation well, the performance of these two algorithms saturates quickly under this scenario. As an alternative, GCN-CNVPS can handle and utilize the complex spatial correlation between ten vehicles and offer an even better performance than a smaller group of cooperative vehicles, proving the scalability of GCN-CNVPS.

C.4.5 Training overhead of Different DL-based CNVPS algorithms: Fig. 8 shows the number of trainable parameters for different DL-based CNVPS algorithms. Because the dimensions of the input layer of MLP-CNVPS increase with the number of time slots, the number of trainable parameters also increases with this number. For the LSTM-CNVPS, the number of trainable parameters remains the same because LSTM-CNVPS can use the same trainable parameters to process the data from different time slots. Moreover, we can observe that the numbers of trainable parameters of MLP-CNVPS and LSTM-CNVPS are comparable. For GCN-CNVPS, although the number of trainable parameters will also increase with the number of time slots because the number of dimensions of the input layer of GCN-CNVPS also increases with the number of time slots, the rate of increase is fairly flat compared to that of MLP-CNVPS. Finally, we can observe that the training overhead of GCN-CNVPS is far less than that of MLP-CNVPS and LSTM-CNVPS. Note that GCN-CNVPS can also significantly outperform MLP-CNVPS and LSTM-CNVPS. Based on the aforementioned observations, we conclude that GCN-CNVPS is an efficient CNVPS solution with a high performance and low training overhead, because both temporal and spatial correlations are well utilized for aiding the GPS refinement during GCN operations, making GCN-CNVPS a potential solution to assisting the GPS refinement in practice.

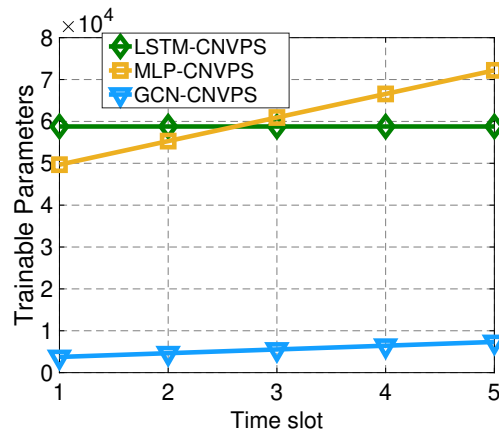


Figure 99. comparison of training overhead of different DL-based CNVPS algorithms.

C.5 Conclusion

In this study, we proposed several cooperative vehicle localization approaches based on the DL technique to provide precise location estimation results. Specifically, MLP-CNVPS can be used to apply an effective data fusion and aid in the GPS refinement. LSTM-CNVPS was developed by further considering the temporal correlation hidden in the multiple time-slot data. Finally, GCN-CNVPS was developed to consider temporal and spatial correlations simultaneously, offering a higher performance and lower training overhead compared to the existing aforementioned algorithms. Moreover, extensive simulations also confirmed the scalability and robustness of the proposed algorithms, making the developed algorithms potential candidates for use in GPS refinement in practice. We also hope that this study will encourage researchers to introduce GCN-based algorithms for efficient vehicular applications.

APPENDIX: D
Dynamic Power Allocation and Virtual Cell Formation for Throughput-Optimal Vehicular Edge Networks in Highway Transportation

Appendix D Dynamic Power Allocation and Virtual Cell Formation for Throughput-Optimal Vehicular Edge Networks in Highway Transportation

D.1 Introduction

Vehicular networking has lately drawn significant attention in wireless networking, particularly for next-generation communication platform, such as beyond 5G systems. The advent of vehicular ad-hoc networking [115] has made it possible to establish communication among vehicles on the road. This has posed as a direct method to share important safety messages among the vehicles using device-to-device like communication. The early development of dedicated short-range communications (DSRC) [138] were designed following IEEE 802.11 physical and medium access layers technologies [275]. However, DSRC uses collision avoidance medium access schemes [213]. Particularly, when network load increases, this creates an extra burden when extreme reliability has to be ensured [24]. The so-called cellular vehicle-to-everything (C-V2X) was developed by the 3GPP as a potential alternative [213] to these limitations of DSRC. In C-V2X there are mainly two radio interfaces, namely the cellular interface (Uu interface) and the sidelink (PC5 interface). VUs maintain their communication with the infrastructure using the Uu interface. On the other hand, they can communicate with each other directly using the PC5 interface. The applications of V2X aim to incorporate both DSRC and C-V2X [101], in reality, and have significantly drawn the attention recently to reduce travel time, traffic congestion, and ubiquitous internet connectivity for smart cities [126].

There are several works in the literature addressing various aspects of vehicular networking. Şahin *et al.* have presented a virtual cell formation for V2X in [271] where vehicles that are in close-proximity can receive downlink multicast data from the transmission points. Gao *et al.* have proposed a deep neural network based resource allocation scheme in [169] where they have used block coordinated descent method and minimized weighted minimum mean square error. Lien *et al.* have considered a local area data network and shown a way to achieve lower latency in the radio access part in [174]. Considering the potential of performing caching at the edge nodes, the authors have used sophisticated tools of stochastic optimization and reinforcement learning (RL) to achieve lower latency using feedback less transmission. He *et al.* have proposed an integrated platform for connected vehicles in [122]. The authors have formulated an integrated platform, in which they have orchestrated a joint networking, caching and computing resource allocation problem, and applied deep reinforcement learning (DRL) techniques.

Tan *et al.* have incorporated both caching and computing in mobility aware vehicular networks in [298]. The authors have shaped vehicle mobility using a naive contact time-based model. Considering both VUs and RSUs have caching and computing capabilities, they have used a DRL framework to find the optimal caching placement and computing resource allocation strategy in this paper. Ye *et al.* have used DRL to allocate radio resources for vehicle-to-vehicle (V2V) communication in [343]. In particular, they have reused the vehicle-to-infrastructure (V2I) uplink channels for V2V transmissions. Distributed vehicular networking resource allocation problems have also been addressed in [173] using multi-agent reinforcement learning. Similar to Ye *et al.*, the authors have reused uplink frequency resources for V2V communications. They have devised a system where their agents can interact with the environment and decide which channel to reuse and V2V transmission power level for V2V communication.

While most of these works address various aspects of V2X communication from the traditional network perspective, in this work, we incorporate user-centric dynamic cell design in a sophisticated software-defined environment to serve the users from multiple sources simultaneously. Particularly, we contemplate a centralized environment where resources can be programmed, controlled and distributed based on the users' demands. As presented in Fig. 100, we consider multiple edge servers are delicately deployed closer to the edge nodes in order to lessen end-to-end latency and improve spectral efficiency. Each of these edge servers is physically connected to a cloud server and controlled by its corresponding ANs. Furthermore, low-powered relay like APs are stationed as RSUs to guarantee ubiquitous connectivity of the VUs. Each of these APs is mesh connected to each of the edge servers. Moreover, we are interested in joint virtual cells design - for each of the scheduled VUs, and optimal beamforming vectors of the low-powered APs. Therefore, in this paper, we address joint user scheduling and power allocation problem in a highly mobile vehicular downlink network from the users' prospect.

To the best of our knowledge, this is the first work to consider software-defined joint user-centric cell formation and power allocation, which ensures reliable communication and maximizing weighted sum rate (WSR) in a highway vehicular platform. Due to the complex combinatorial nature of the formulated optimization problem, it is challenging to solve the problem via traditional optimization methods. Thus, we propose a distributed Q-learning based RL solution to obtain optimal WSR and validate our results with genie-aided optimal, baseline single agent RL

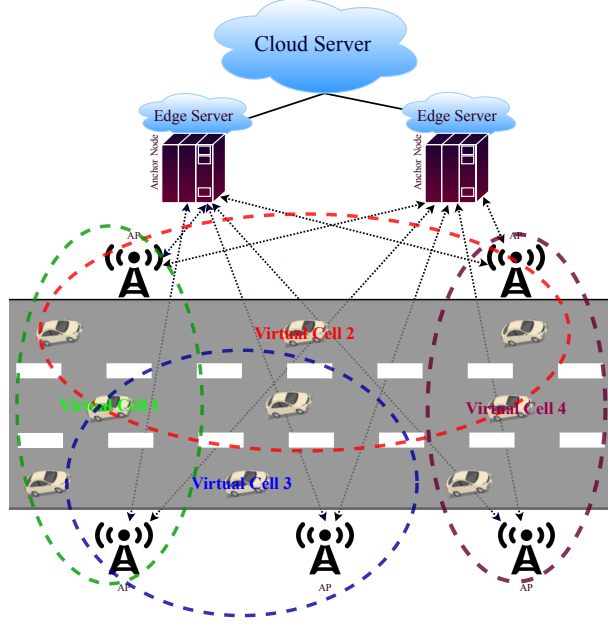


Figure 100. User-centric vehicular edge networking.

(SARL), multi-agent RL (MARL) and other baseline schemes. The rest of the paper is organized as follows. Section D.2 presents our system model with vehicle node distributions, SDV2I communication and problem statements. The proposed RL solution is described in Section D.3 followed by results and discussions in Section D.4. Finally, Section D.5 concludes the paper.

D.2 System Model and Problem Formulation

We present our software-defined system model, followed by the node distributions, communication model and dynamic user-centric cell formation problem in this section.

D.2.1 Software-Defined System Model: We consider highly mobile autonomous VUs are moving on the road. Let us denote the VU set by $\mathcal{U} = \{u_1, u_2, \dots, u_U\}$, where $U \in \mathbb{Z}^+$. Various low-powered APs are deployed in the surrounding geographic region. Let the set of APs be denoted by $\mathcal{A} = \{a_1, a_2, \dots, a_A\}$, where $A \in \mathbb{Z}^+$. The VUs move on the road and each VU establishes its connection with the network via these APs. We assume that all of the APs are physically connected to edge servers. Note that, in reality, the number of such connections will be confined into a small group due to geographic locations of these edge nodes. Furthermore, each of the edge servers is controlled, programmed and operated by its respective AN. Let us denote AN by $b_l \in \mathcal{B}$. In other words, there exists $|\mathcal{B}|$ numbers of edge servers each of which can be expressed by the identical notation of its AN. Each of the edge servers has a fixed and limited radio spectrum assigned by the cloud server. Let W_l [Hz] denote the available radio resources of the edge server b_l . Considering an open-loop communication system, we assume that the channel state information (CSI) is perfectly known at each of the ANs. The ANs can form and schedule the beamforming weights of the APs for each of the virtual cells. Therefore, our system model is based on sophisticated SofAir [180], where the ANs control, create and assign resource slices to the APs based on user's demands and thus, enhances the overall spectral efficiency.

In order to ensure reliability and ubiquitous connectivity, we assume a VU can associate with multiple APs that are in its communication region. That is, in comparison to the conventional network-centric approach, we consider user-centric communication by formulating virtual cells for the scheduled users by associating each of them to multiple APs. Some patterns of forming virtual cells are shown by the dotted ellipses in Fig. 100. Without any loss of generality, let us denote a user and an AP by $u_i \in \mathcal{U}$ and $a_j \in \mathcal{A}$, respectively. Due to a user-centric approach, let $\mathcal{A}_i(t)$ denote the set of APs that a VU u_i can associate to, in time slot t . Furthermore, we denote the VU-AP association by the following indicator function:

$$a_i^j(t) = \begin{cases} 1, & \text{if AP } a_j \text{ is associated with VU } u_i \\ 0, & \text{otherwise.} \end{cases} \quad (\text{D.1})$$

Moreover, an AP might be connected to multiple VUs at the same time. Let us further denote the set of VUs connected to an AP a_j at time slot t by the set $\mathcal{U}_j(t)$. We then have the following indicator function:

$$u_j^i(t) = \begin{cases} 1, & \text{if VU } u_i \text{ is associated with AP } a_j \\ 0, & \text{otherwise.} \end{cases} \quad (\text{D.2})$$

Hence, $\mathcal{A}_i(t)$ denotes the set of APs that VU u_i is connected to whereas, $\mathcal{U}_j(t)$ denotes the set of VUs connected to the AP a_j in a given time slot.

D.2.2 Road Model and Node Distributions: We consider a straight three-lane one-way road structure without any intersection as our region of interest (ROI). Specifically, we consider the freeway case of 3GPP [3]. However, our modeling can be extended to complex practical road modeling. We are interested in establishing a communication framework for the V2X platform where the vehicle models are independent of road structure. The lane can be denoted by L_m , where $m \in \{1, 2, 3\}$ in our case. We deploy VUs and APs following uniform distributions while maintaining a safety distance between two VUs. The method of updating mobility is described in Algorithm 1. Note that the Doppler effect has not considered in this paper and will be examined in our future work.

Algorithm 1: Vehicular Road Traffic Modeling

```

1: Input: Total number of VUs and lanes for each time step,  $t = 1, 2, \dots, T_n$  do
   for each lane do
     for each vehicle do
       |
       | Update vehicle's position by adding linear displacement based on its velocity { If new position is outside the ROI,
       | TERMINATE}
5: Return: All vehicles' positions

```

D.2.3 Software-Defined Vehicle-to-Infrastructure Communication: We assume that the VUs are equipped with a single antenna, whereas, each of the low-powered APs is equipped with a N_j number of antennas. Unless mentioned otherwise, we assume an omnidirectional antenna for both VU and APs. Furthermore, with a slight abuse of notation, we represent the set of APs in $\mathcal{A}_i(t)$ by the set $\{a_{1,i}(t), a_{2,i}(t), \dots, a_{|\mathcal{A}_i(t)|,i}(t)\}$, where $|\cdot|$ represents cardinality of set $\mathcal{A}_i(t)$. Moreover, $|\mathcal{A}_i(t)| \leq A$ i.e., the total number of APs assigned to the virtual cell i of VU u_i has to be less than or equal to the total number of available APs in the network for all time slot t .

We model the wireless channel, between AP and VU, as an independent quasi-static flat fading model during a basic time block. Let us denote the channel response at a VU u_i from the AP a_j by $\mathbf{h}_{a_j^i}(t) = [h_{ij_1}(t), h_{ij_2}(t), \dots, h_{ij_{N_j}}(t)]^T$, where $h_{ij_p}(t)$ denotes the channel between u_i and the p^{th} antenna of AP a_j at time t . Then, the channel response at the VU u_i from all APs is represented as follows:

$$\mathbf{h}_i(t) = [\mathbf{h}_{a_1^i}^T(t), \mathbf{h}_{a_2^i}^T(t), \dots, \mathbf{h}_{a_A^i}^T(t)]^T = \mathbf{D}_i(t)\mathbf{\rho}_i(t)\mathbf{\tau}_i(t) \in \mathbb{C}^{N \times 1}, \quad (\text{D.3})$$

where $\mathbf{D}_i(t)$, $\mathbf{\rho}_i(t)$ and $\mathbf{\tau}_i(t) \sim CN(\mathbf{0}, \mathbf{I}_N)$ are large scale fading, *log*-Normal shadowing and fast fading channel vectors, respectively. Note that channels are modeled following appropriate measures listed in [3]. Moreover, $N = \sum_{j=1}^A N_j$ denotes the total number of antennas in all APs.

We assume linear downlink beamforming in our SD V2I platform. Let us denote the beamforming vector for VU u_i at AP a_j by $\mathbf{w}_{a_j^i}(t) \in \mathbb{C}^{N_j \times 1}$ in time t . Then, the beamforming vector to VU u_i can be denoted by $\mathbf{w}_i(t) \triangleq [\mathbf{w}_{a_1^i}^T(t), \dots, \mathbf{w}_{a_A^i}^T(t)]^T \in \mathbb{C}^{N_i \times 1}$. Furthermore, the entire network beamforming design can be denoted by $\mathbf{W}(t) \triangleq \{\mathbf{w}_1(t), \dots, \mathbf{w}_U(t)\}$. Now, let us also denote the unit powered intended signal for VU u_i by $x_i(t) \in \mathbb{C}$. Therefore, we have to satisfy $\mathbb{E}[x_i^H(t)x_i(t)] = 1$ all the time. Furthermore, applying the beamforming vector, the transmitting signal of the AP a_j is denoted as $\mathbf{s}_j(t) = \sum_{i=1}^U \mathbf{w}_{a_j^i}(t)x_i(t)$.

Therefore, the received signal at the VU u_i is then calculated as follows:

$$y_i(t) = \sum_{a_j \in \mathcal{A}} \mathbf{h}_{a_j}^H(t) \mathbf{s}_j(t) + \eta_i(t) \mathbf{h}_i^H(t) \mathbf{w}_i(t) x_i(t) + \sum_{u_{i'} \in \mathcal{U} \setminus u_i} \mathbf{h}_i^H(t) \mathbf{w}_{i'}(t) x_{i'}(t) + \eta_i(t) \quad (\text{D.4})$$

where $\eta_i(t) \sim CN(0, 1)$ denotes the received noise which is zero mean circularly symmetric Gaussian distributed with variance σ^2 .

D.2.4 User-Centric Dynamic Cell Formation: With our analysis and vehicular traffic modeling, as presented in D.2.2, we now aim to derive the instantaneous achievable rate at the VU. At first, we calculate the signal-to-interference-plus-noise ratio (SINR) as follows:

$$\gamma_i(\mathbf{W}(t)) = \frac{|\mathbf{h}_i^H(t) \mathbf{w}_i(t)|^2}{\sigma^2 + \sum_{u_{i'} \in \mathcal{U} \setminus u_i} |\mathbf{h}_i^H(t) \mathbf{w}_{i'}(t)|^2} \quad (\text{D.5})$$

Considering time division duplexing (TDD) operated system, we thus calculate the instantaneous achievable data rate for VU u_i as follows:

$$R_i^t(\mathbf{W}(t)) = (1 - \kappa) \log_2(1 + \gamma_i(\mathbf{W}(t))), \quad (\text{D.6})$$

where κ represents spectral efficiency loss due to signaling at the APs. Note that if a user is scheduled during the transmission time slot, the beamforming vector $\mathbf{w}_i(t)$ is nonzero, thus the rate is nonzero as well. On the other hand, if a user is not scheduled, the beamforming vector for that user should be zero leading to a zero achievable rate.

Furthermore, as multiple APs are serving each of the scheduled users, the backhaul resource consumption by each of those users should also be carefully calculated. As such, next, we calculate the backhaul resource consumption [66] as follows:

$$C_i(t) = \left\| \left[\left\| \mathbf{w}_{a_1^i}(t) \right\|_2, \dots, \left\| \mathbf{w}_{a_A^i}(t) \right\|_2 \right] \right\|_0 R_i^t(\mathbf{W}(t)), \quad (\text{D.7})$$

where $\|\cdot\|_0$ represents the total number of nonzero elements in a vector and commonly referred as l_0 -norm.

Now, due to resource constraints, we may not serve all users at the same time. Therefore, there will be certain restrictions on the number of active users in the VU set $\mathcal{U}$. However, recall that our formulated rate calculation in equation (D.6) can also be used to design the user scheduling. We intend to serve all active users in $\mathcal{U}$ in a transmission time slot by forming virtual cells for each of the users and dynamically selecting the transmission power of the APs. We aim to find optimal user-centric cell formation and beamforming weights calculation for the APs in our objective function. The question that we try to answer is - *what are the optimal user associations and APs transmission powers that maximize the throughput in our SD controlled highly mobile vehicular network?* A naive approach would be serving a user from as many APs as possible with the maximum transmission powers of the APs. However, transmitting to a particular VU from the APs with maximum transmission power will severely impact the SINR performances of the other active VUs. Therefore, it is essential to know the optimal transmission power of the APs for each of the active VUs.

We present our joint optimization problem as follows:

$$\begin{aligned} \textbf{Find:} & \quad a_i^j(t), u_j^i(t), \mathbf{w}_{a_j^i}(t), \quad \forall i \in \mathcal{U}, j \in \mathcal{A} \\ \textbf{Maximize} & \quad \sum_{i \in \mathcal{U}} \zeta_i(t) C_i(t) \end{aligned} \quad (\text{D.8a})$$

$$\textbf{Subject to} \quad 1 \leq |\mathcal{A}_i(t)| \leq A, \quad \forall i \in \mathcal{U} \quad (\text{D.8b})$$

$$\gamma_i(\mathbf{W}(t)) \geq \gamma_i^{\min}, \quad \forall i \in \mathcal{U} \quad (\text{D.8c})$$

$$\sum_{i=1}^U \left\| \mathbf{w}_{a_j^i}(t) \right\|_2^2 \leq P_j^{\max}, \quad \forall j \in \mathcal{A} \quad (\text{D.8d})$$

$$a_i^j(t) \in \{0, 1\}, u_j^i(t) \in \{0, 1\}, \quad (\text{D.8e})$$

where $\zeta_i(t)$, $\gamma_i^{\min}$ and $P_j^{\max}$ are the weights of the data rate of user u_i at time t , minimum SINR requirement for reliable communication and maximum allowable transmit power of AP a_j , respectively. Note that constraint (D.8b) ensures that our user-centric virtual cell contains more than one AP to form the cluster. Constraint (D.8c) ensures the obtained

SINR is greater than a minimum threshold. Moreover, constraint (D.8d) limits the total transmit power of AP a_j to be at maximum P_j^{max} .

Due to the l_0 norm, the formulated problem is not suitable to be solved using a gradient-based algorithm. Furthermore, due to the combinatorial nature of the originated problem, it is extremely hard to solve within a short period. Note that if we know all $a_j^i(t)s - \forall j \in \mathcal{A}$, we can figure out the $u_j^i(t)s$ using equations (D.1-D.2). Therefore, for each of the AP, there are $2^U - 1$ possible combinations, only for the VU-AP associations, in a single time-slot. Besides, for each of these associations, the AP has to select the power level for each of the active users. Moreover, in a centralized controlled environment, the centralized agent needs to make a central decision for all such AP-VU associations and power levels selection pairs. As such, it is obvious that as the number of APs and VUs increases the complexities increases exponentially. Therefore, we employ an elegant machine learning approach to solve the problem in what follows.

D.3 Reinforcement Learning-Based Vehicular Edge Slicing Mechanism

In this section, we discuss the problem-solution from the RL perspective. We first clearly state the state, action, and reward of the RL agent. Then we present our learning algorithms.

D.3.1 State: The state-space contains all channel state information $\mathbf{H}^t$. It also contains the geographic locations of the VUs and APs. Let us denote the positions of the VUs and APs at state $\mathbf{s}_t$ by $\mathbf{X}_i^t$ and $\mathbf{X}_j^t$, respectively. Therefore, we denote our state space as follows:

$$\mathbf{s}_t = \{\mathbf{X}_i^t, \mathbf{X}_j^t, \mathbf{H}^t\}. \quad (\text{D.9})$$

D.3.2 Action: The action space contains the VU-AP association indicator functions followed by the beamforming vectors for the selected VU-AP associations.

$$\mathbf{a}_t = \left\{ a_j^i(t) \forall i \in \mathcal{U}, \mathbf{w}_{a_j^i}(t) \forall j \in \mathcal{A} \right\} \quad (\text{D.10})$$

Notice that, in equation (D.10), the RL agent needs to take two action sets i.e., VU-AP associations and beamforming weights. However, both of these actions cannot be performed at the same time. Simply put, for deciding the optimal beamforming weights, the agent needs to know the VU-AP associations. Therefore, the action set can be thought of as a twin step process. At first, the RL agent needs to decide the VU-AP associations. Based on that decision, it then can allocate each AP's transmission power for all of the VU that are being served by the respective AP. Therefore, we divide the action space into twin scales as described below.

Considering an open-loop system - one-shot transmission, to ensure reliability and increase the user data rate, we have considered serving a scheduled VU from multiple APs. If a user is scheduled to be served, we then design the beamforming vectors of the APs for that particular user. Now, note that we assume perfect CSI is known at the AN. As such, we model the beamforming weights using the following equation:

$$\mathbf{w}_{a_j^i}(t) = \frac{\mathbf{h}_{a_j^i}(t)}{\|\mathbf{h}_{a_j^i}(t)\|_2} \times \sqrt{P_{a_j^i}(t)}, \quad (\text{D.11})$$

where $\mathbf{h}_{a_j^i}(t)$ is the wireless channel information from AP a_j to VU u_i and $P_{a_j^i}(t)$ is the allocated transmission power of AP a_j to transmit to VU u_i . Therefore, we rewrite the action space as:

$$\mathbf{a}_t = \left\{ a_j^i(t) \forall i \in \mathcal{U}, P_{a_j^i}(t) \forall i \in \mathcal{U} \& j \in \mathcal{A} \right\}. \quad (\text{D.12})$$

Now, instead of continuous power level, we divide the APs transmission power level into multiple discrete levels. Particularly, we divide $P_{a_j^i}(t)$ into 4 levels (e.g., $P_{a_j^i}(t) \in \{5, 10, 15, 20\}$ dBm). In other words, each AP can select its transmission power to serve a user from one of these power levels. Therefore, our objective function is still the same as presented in equation (D.8). We formulate the beamforming vectors using the optimal power selection and equation (D.11).

D.3.3 Reward: Without any loss of generality, we define the weighted sum rate as the reward function for our learning algorithm. We also ensure that each of the users receives the minimum SINR threshold for a chosen

action; otherwise, we return a zero reward. Accordingly, the reward function is given as follows:

$$r_t = \begin{cases} \sum_{i \in \mathcal{U}} \zeta_i(t) C_i(t), & \text{if } \gamma'_i(\mathbf{W}(t)) > \gamma_i^{\min} \forall i \in \mathcal{U} \\ 0, & \text{otherwise.} \end{cases} \quad (\text{D.13})$$

D.3.4 Single Agent Reinforcement Learning (SARL): Q -learning is a model-free RL framework [329] which takes the state and action into account and solve hard optimization problem such as equation (D.8) efficiently. In each state $\mathbf{s}_t$ the agent takes an action $\mathbf{a}_t$ from which it gets a reward r_t and the environment transit to the next state $\mathbf{s}_{t+1}$. The governing equation of Q -learning is shown in the following:

$$Q(s_t, a_t) \leftarrow (1 - \alpha)Q(s_t, a_t) + \alpha \left(r_t + \gamma \max_{\mathbf{a}} Q(s_{t+1}, \mathbf{a}) \right), \quad (\text{D.14})$$

where α and γ are learning rate and discount factor, respectively. Our learning algorithm for SARL is presented in Algorithm 2.

Algorithm 2: Q - learning based RL Algorithm

- 1: **Initialize:** For all possible states and actions generate random $\mathbf{Q}(\mathbf{s}_t, \mathbf{a}_t)$ table **for each episode do**
 - 2: Initiate the environment
 - 3: Generate $\mathbf{s}_t = \{\mathbf{X}_i^t, \mathbf{X}_j^t, \mathbf{H}^t\}$ **while not terminated do**
 - 4: Take action using ϵ -greedy policy
 - 5: Calculate reward, r_t , transit to next state $\mathbf{s}_{t+1}$
 - 6: Update Q table following equation (D.14)
 - 7: $\mathbf{s}_t \leftarrow \mathbf{s}_{t+1}$ {If $\mathbf{s}_t$ is the terminal state}
-

D.3.5 Multi-agent Reinforcement Learning (MARL): In MARL, multiple agents can take their individual actions and get an overall centralized reward for their joint decisions. Liu *et. al.* have recently presented a MARL framework in [186] in which each agent has its own Q -table and can take action independently. Particularly, following the ϵ -greedy policy, if the value of the random variable is greater than ϵ , the authors have chosen the action of the n th agent using the following equation:

$$a_n^t = \arg \max_a \left(\sum_{1 \leq j \leq N} Q_j^t(s_j^t, a) \right), \quad (\text{D.15})$$

where $j = 1, \dots, N$ represents the cooperating agents. The update rule for the n th agents follows the following equation [186]:

$$Q_n(s_n, a_n) \leftarrow (1 - \alpha)Q_n(s_n, a_n) + \alpha \left(r_n(s_n, \bar{a}) + \gamma \max_{b \in A_n} Q_n(s_n', b) \right). \quad (\text{D.16})$$

D.3.6 Distributed SARL with Multi-agent Learning (SARL-MARL Collaboration): While SARL is the baseline RL scheme, it may suffer to attain the best performance if the action and state space are too large. In such a platform MARL can be used to shrink the number of action space. However, whether MARL will achieve the optimal performance is still questionable as each agent takes its decision independently. Although, Liu *et. al.* [186] have considered collaboration among the agents, we validate through simulation results that this scheme fails to attain the best performance in our specific problem. As an alternative, we incorporate the concept of distributed learning. Since a single agent RL framework has to evaluate all possible actions, we consider dividing the action space into multiple agents. We use individual Q -table and keep track of the global best performance. Note that the number of possible states for all agents are still the same as SARL, we are only evaluating the performance from segmented action spaces.

Let us denote the number of agents by N .

Then, the dimension of the Q -table for each of the agents is $\mathbb{R}^{S \times A/N}$, where S and A represents the size of the state space and action space, respectively. Note that we selected N such a way that $A/N \in \mathbb{Z}^+$. In each of the state $\mathbf{s}_t$, each of these N agents takes their action following the same methodology as the baseline Q -learning. Let us denote $\mathbf{Q}_{central} \in \mathbb{R}^S$ a centralized vector that stores the global best action in each of the states. In each of the time step, we

update the $\mathbf{Q}_{central}$ using the following equation:

$$\mathbf{Q}_{central}[\mathbf{a}_t] \leftarrow \begin{cases} \mathbf{Q}_{central}[\mathbf{a}_t], & \text{if any } r_t[\mathbf{a}_t] > r_t[\mathbf{a}_t^{old}], \forall \text{agents} \in N \\ \mathbf{Q}_{central}[\mathbf{a}_t^{old}], & \text{otherwise.} \end{cases} \quad (\text{D.17})$$

Note that each of the agents follows and updates its action and Q -table according to the baseline SARL. The detailed procedure of our distributed SARL with multi-agent learning is presented in Algorithm 3.

Algorithm 3: SARL-MARL: Distributed SARL

- 1: **Initialize:** Total number of agents, N , divide the large action space into N small sets.
 - 2: For all possible states and action sets generate random $\mathbf{Q}_l(\mathbf{s}_t, \mathbf{a}_t)$ tables, where $l \in N$ represents the agent id.
 - 3: Generate $\mathbf{Q}_{central} \in \mathbb{R}^S$ randomly
 - 4: **for each episode do**
 - 5: Initiate the environment, generate $\mathbf{s}_t = \{\mathbf{X}_i^t, \mathbf{X}_j^t, \mathbf{H}^t\}$
 - 6: **while not terminated do**
 - 7: **for each** $l \in N$ **do**
 - 8: Observe the environment; choose $\mathbf{a}_t$, based on the observation, following ϵ -greedy policy; receive reward r_t ; update its Q -table using equation (D.14)
 - 9: **if** $r_t > \text{reward using } \mathbf{Q}_{central}[\mathbf{a}_t]$ **then**
 - 10: update $\mathbf{Q}_{central}$ using equation (D.17)
 - 11: $\mathbf{s}_t \leftarrow \mathbf{s}_{t+1}$ {If $\mathbf{s}_t$ is the terminal state}
-

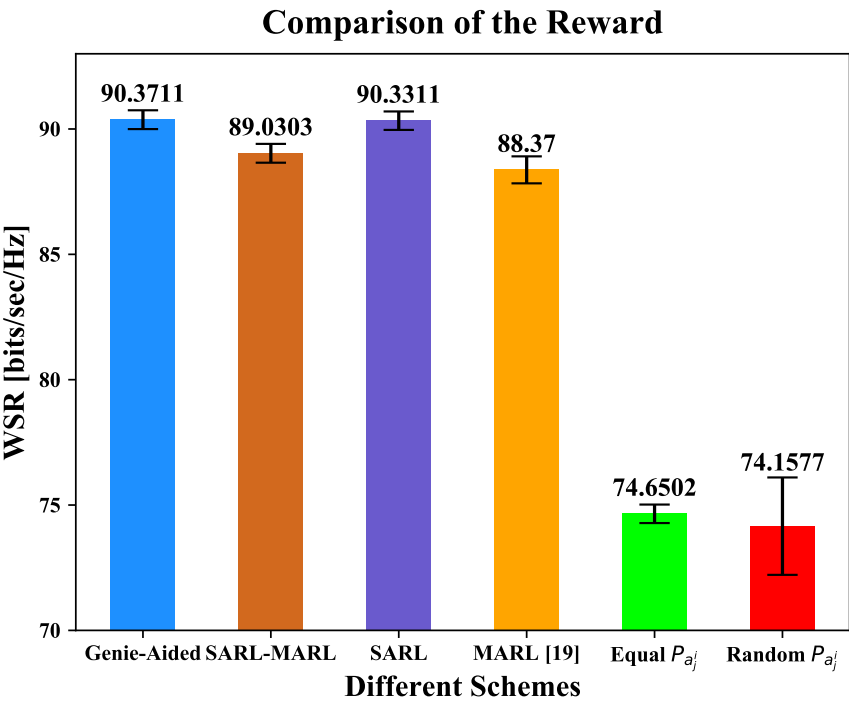
D.4 Performance Evaluation

We consider 500 meters of a three-lane one-way freeway as our ROI. Vehicle's new position is generated by adding linear displacement with VU velocity of 140 km/h as per [3]. The channel model and related parameters are also chosen as specified in [3]. In order to keep a tractable state space, we consider updating it after every 100 milliseconds. Furthermore, for the ease of simulation, we consider a full buffer network model in which each of the APs serves all VUs simultaneously. Note that our proposed problem solution can work in other scheduling algorithms as well. As we are not adopting any actual scheduling schemes, we consider full buffer scenarios with $\zeta_i(t) = 1, \forall i \in \mathcal{U} \& t$. We consider 1 AN, 3 APs and 3 users. While the VUs are dropped uniformly in each lane, the APs are placed 150 meters apart fixed locations. We have assumed 8 antennas per AP. For a tractable state space, we have considered that, at a given time step, all VUs are in the same x locations - while they have different y locations. We also have $\gamma_i^{min} = 10$ dB $\forall i \in \mathcal{U} \& t$ and $\kappa = 0.1$.

For the SARL, MARL and SARL-MARL collaborative algorithms, we have considered $\gamma = 0.8$. Besides, the value of both ϵ and α are decayed linearly from 1 to 0.01 in each episode. Also, we have considered 3 APs as independent agents for the MARL algorithm of Liu *et. al.* [186] and we have used $N = 4$ for our SARL-MARL distributed learning algorithm. For both SARL and MARL cases, we have trained our models for 1×10^5 episodes while we only train our model in 2.5×10^4 episodes in the SARL-MARL distributed learning case. In order to validate the results of each of these algorithms, we have compared the results with the *genie-aided: optimal* solution. We have also used two baseline schemes, namely, (1) *random power*: each AP randomly choose its transmitting power from $\{5, 5, 15\}$ and (2) *equal power*: each AP transmit to all VUs using P_j^{max}/U dBm power.

We compare the average rewards of all of these schemes after running 250 test episodes in Fig. 63. Our proposed SARL-MARL, baseline SARL, and MARL algorithms deliver average per VU reward of 29.68, 30.11, and 29.46 bits/sec/Hz. These are nearly identical to the genie-aided optimal per VU reward of 30.12 bits/sec/Hz. However, recall that we have trained both SARL and MARL for 10^5 episodes, whereas the proposed SARL-MARL distributed learning algorithm has been trained on only 2.5×10^4 episodes. The performance of the equal and random power allocation schemes are, as expected, worse than the RL schemes. With regard to user fairness, our RL schemes and reward function always ensure that each of the users receives a fair data rate. Since we return zero rewards in the case that any of the user's SINR is below the threshold level, we expect that our RL agents learn this pattern quickly. This

Performance comparisons of different schemes



User fairness

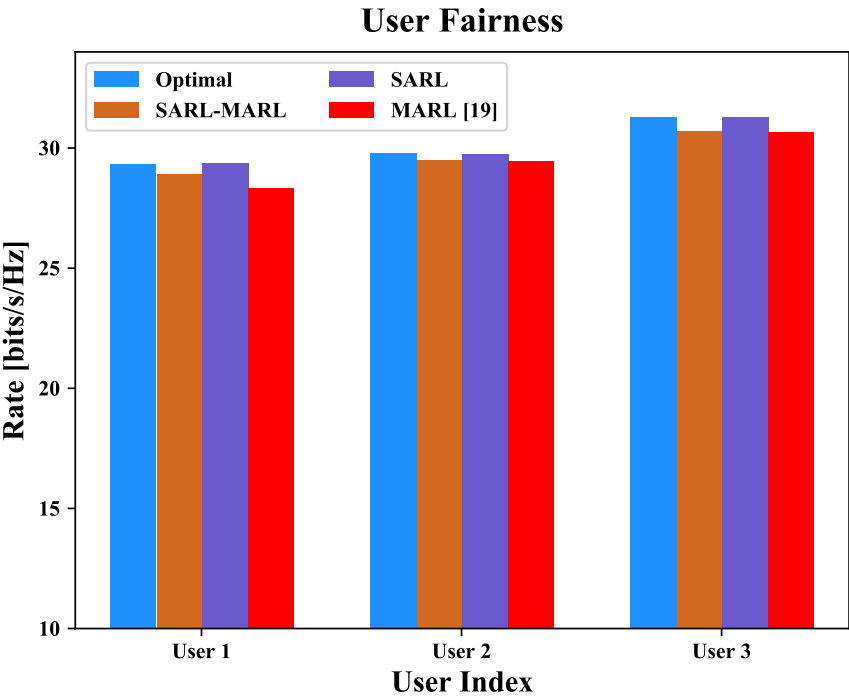


Figure 101. Performance comparisons: AP coverage radius = 250 m, $\gamma_i^{min} = 10$ dB.

is also verified by our simulation results in Fig. 63.

We further consider the impact of the reliability threshold. Note that, in our optimization problem, we have set the reliability constraint that each of the users has to get a minimum SINR threshold to ensure reliability. This, therefore, guarantees that regardless of the environment, our RL will learn to allocate resources such a way that each of the VUs receives at least γ_i^{min} SINR. Furthermore, Fig. 102 indicates that as this threshold increases, the network should experience difficulties in achieving this demand for all of the users. Both Figs. 64 confirm that our proposed distributed SARL multi-agent learning (SARL-MARL) algorithm reaches near-optimal results compare to that of Liu *et. al.*'s MARL and other baseline schemes. The performance gap between the optimal and the proposed SARL-MARL results are very close. Besides, the gap between our proposed solution and other baseline schemes are hugely evident as the reliability threshold increases.

Finally, we show the impact of the coverage radius of the APs in Fig. 103. Note that a VU can only be served if its in the coverage region of the AP. Therefore, as the coverage radius of the AP increases, more VUs can be served by that AP. As such, the expected sum rate of the user should increase, if the power levels of the APs are chosen appropriately with the increase of its coverage radius. This is also reflected and validated in our result presented in Fig. 103.

D.5 Conclusion

In this paper, we have presented an efficient way to dynamically allocate the transmission power of the APs and virtual cell formation for the VUs in user-centric vehicular networks. Using well-bred machine learning algorithms, we have demonstrated that the original hard combinatorial problem can be solved efficiently. Furthermore, as the numbers of possible states and actions increase, the traditional SARL suffers to behave optimally due to the curse of dimensionality. While MARL requires quite a large number of training episodes to attain near-optimal performance, the proposed SARL-MARL can achieve similar performance within a nominal number of training episodes.

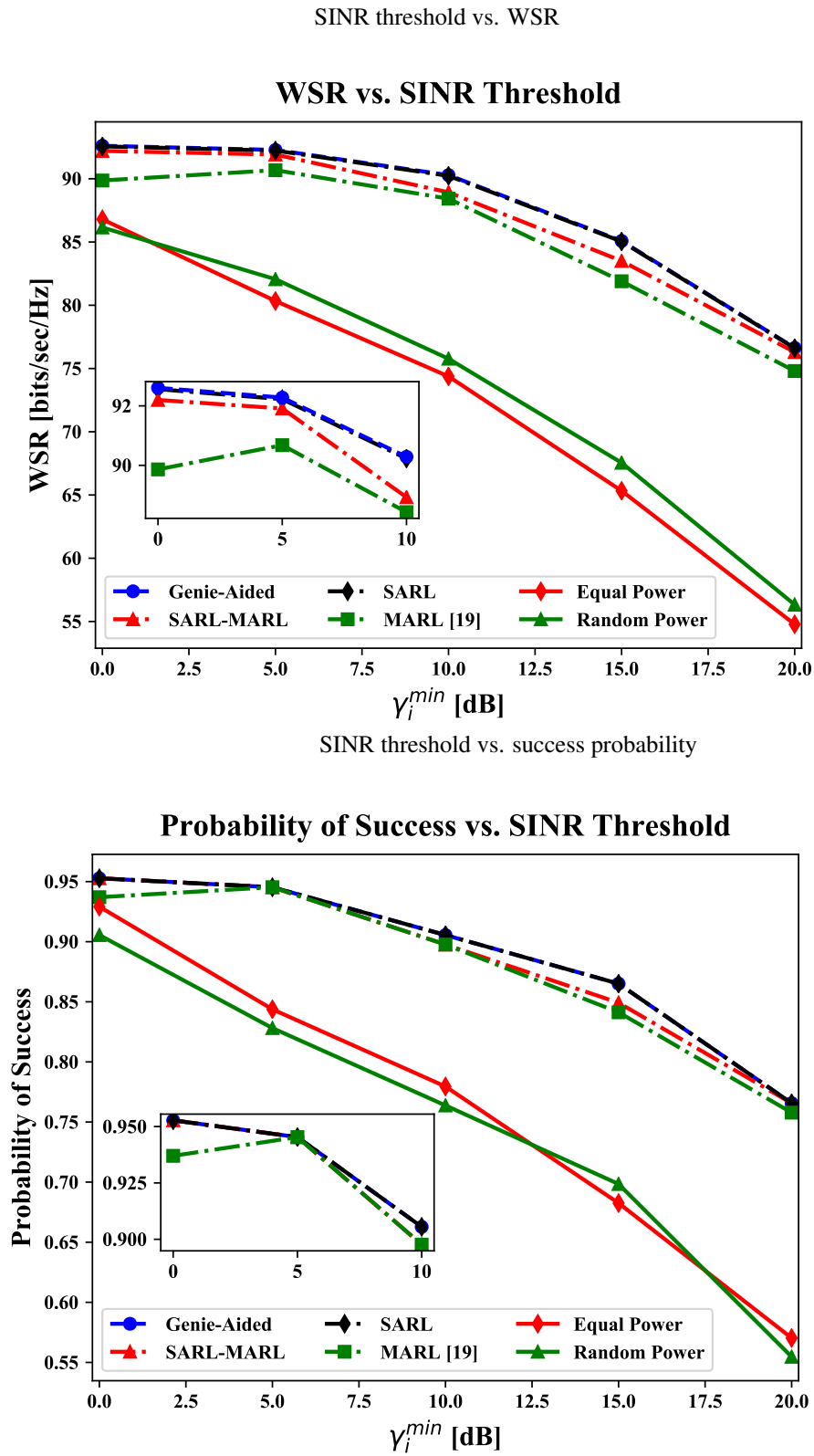


Figure 102. Impact of the SINR threshold.

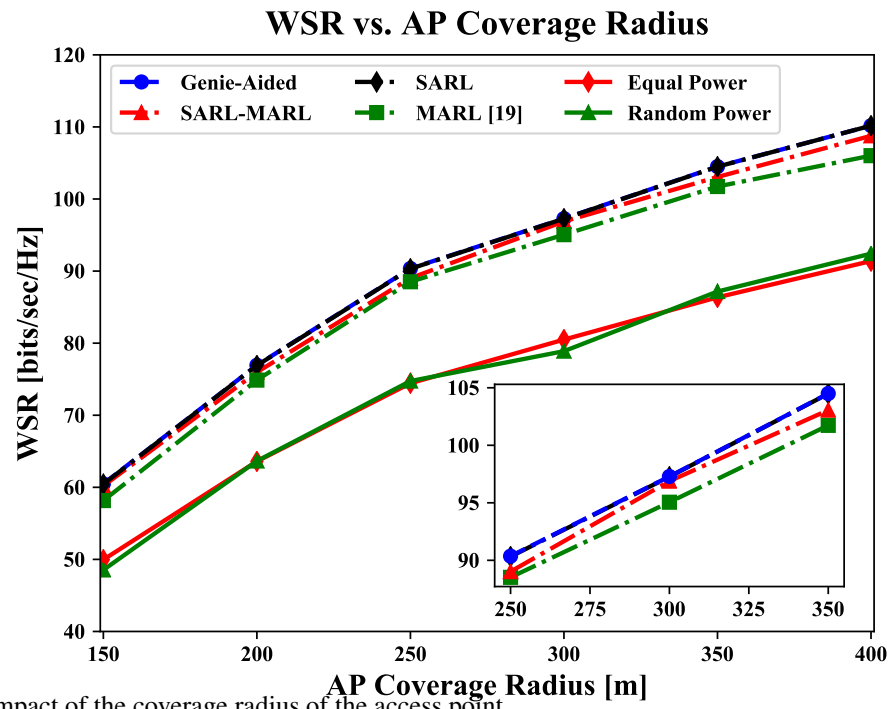


Figure 103. Impact of the coverage radius of the access point.

APPENDIX: E
Eco-Vehicular Edge Networks for Connected Transportation: A Distributed Multi-Agent Reinforcement Learning Approach

Appendix E Eco-Vehicular Edge Networks for Connected Transportation: A Distributed Multi-Agent Reinforcement Learning Approach

E.1 Introduction

User-centric communication has drawn significant attention lately. To ensure a better quality of service (QoS) and appease the data-hungry users, more networking components are being shifted towards the network edges day by day. Vehicular networking, on the other hand, has also been evolving from the rudimentary phase to an intelligent transportation system (ITS) to guarantee public safety, lessen congestion, reduce travel time and better QoS of the vehicle users (VUs). An advanced ITS can undoubtedly save countless lives by assuring ubiquitous connectivity and well-measured timely road hazard alerts, thus, increasing the quality of experience of the VUs. Motivated by this, several governing bodies, such as - the United States Department of Transportation in the USA [4, 5], are heavily investigating more of vehicle-to-everything (V2X) communication.

Novel technologies, such as dedicated short-range communications (DSRC), cellular-V2X (C-V2X), etc., are being deemed to be coupled together [101] to induce an intelligent solution in this sector. Note that while DSRC is an IEEE 802.11 based earlier technology, C-V2X was developed and introduced by 3GPP's Release 14 for basic safety message delivery in vehicular communication [351]. The later releases of 3GPP focus on a more evolved system design with an advanced safety measure in addition to higher throughput, guaranteed reliability, and reduced latency. VUs move fast on the highway causing frequent handovers for V2I communication. Within a very short period, the received signal strength, at the downlink VUs, can deteriorate severely in traditional network-centric communication infrastructure. Therefore, V2I communication is notably problematic for connected transportation. A potential solution to these problems should ensure universal connectivity, reliability, higher throughput, and lower latency. In addition to that, energy-efficiency (EE) should also be considered as green communication has shown its emergency rigorously lately [129, 136].

In the literature, there exist several works [75, 98, 106, 173, 271, 343] addressing diverse aspects of vehicular networks. A downlink multicasting scenario for close-proximity vehicles was acknowledged in [271]. The author, first, created a group of vehicles as a hotspot and served the hotspot users from a single transmission point. Ye *et al.* proposed a vehicle-to-vehicle (V2V) radio resource management (RRM) method in [343] where they used deep reinforcement learning (DRL) to scrutinize the reuse of the uplink radio resources for effective V2V communication. A similar approach was also considered by Liang *et al.*, in [173], for V2V applications using multi-agent RL (MARL). Ding *et al.* considered RRM for vehicular networks in [75]. Although the authors considered virtual cell member association and RRM in their problem formulation, they did not consider user mobility. Note that we are considering highly mobile VUs for connected transportation, where each of the parameters needs to be chosen optimally in each transmission time interval (TTI). Therefore, our work is fundamentally different than a single snapshot-based static user-centric approach in [75].

Gao *et al.* proposed a joint admission control and resource management scheme, for both static and vehicular users, in [98]. Using the Lyapunov optimization technique, the authors showed a way to increase network throughput from the traditional network-centric approach. Guleng *et al.* considered a Q -learning based solution for V2V communication in [106]. They used a two-staged learning process for minimizing overall latency and maximizing the network throughput. In our previous work [248], we considered a throughput-optimal vehicular edge network for highway transportation, in which we achieved a maximum weighted sum rate using RL. While the studies in [75, 98, 106, 173, 248, 343] aimed at optimizing the network throughput, they did not address energy consumption issues in vehicular edge networks for smart and connected transportation.

Different from the existing studies, this paper focuses on uncovering an energy-efficient solution for user-centric and reliable vehicular edge networks in connected transportation. Particularly, we express a joint virtual cell formation and power allocation problem for highly mobile VUs in a sophisticated SD environment. In a freeway road environment, we delicately deploy various edge servers to obtain the users' demands by serving a VU from multiple low-powered access points (APs), as presented in Fig. 104. Although such an infrastructure enhances end-to-end latency and increases the reliability of the network, system complexities also increase. Furthermore, as multiple APs serve each VU, it is essential to optimally form virtual cells for the users and allocate the optimal transmission powers of these APs. While our joint formulation addresses these, it is a hard combinatorial optimization problem. Therefore, we use a model-free distributed MARL (D-MARL) solution that can effectively formulate the virtual cell and slice the resources.

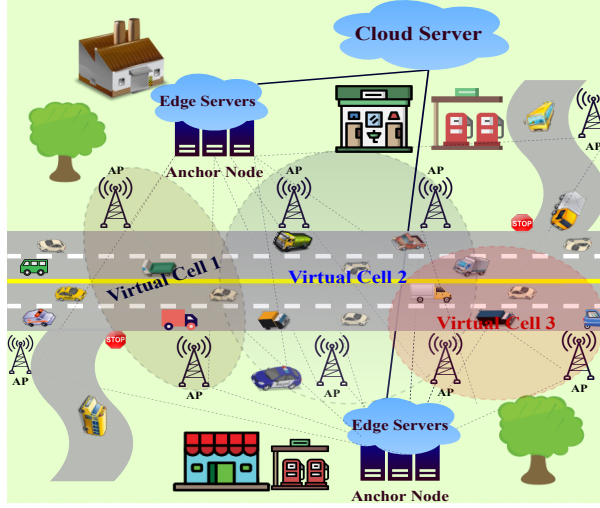


Figure 104. Energy-efficient user-centric vehicular edge network.

To the best of our knowledge, this is the first work to consider a reliable energy-efficient user-centric software-defined vehicular edge network for connected transportation. The rest of the paper is organized as follows: our software-defined network and problem formulation are presented in Section E.2. An efficient RL solution for resource slicing is presented in Section E.3. Section E.4 presents the results and findings. Finally, Section E.5 concludes the paper.

E.2 Software-Defined Vehicular Edge Networks

We present our software-defined vehicular edge network model, followed by the problem formulation, in this section.

E.2.1 Software-Defined System Model: Following the freeway case of 3GPP [3], in this paper, we consider a three-lane one-way road structure¹ as the region of interest (ROI). Highly mobile autonomous VUs, denoted by $\mathcal{U} = \{u_1, u_2, \dots, u_U\}$, where $U \in \mathbb{Z}^+$, move on the road. Besides, several low-powered APs, denoted by $\mathcal{A} = \{a_1, a_2, \dots, a_A\}$, where $A \in \mathbb{Z}^+$, are also deployed along the roadsides in order to maintain ubiquitous connectivity. In addition to that, various edge servers - controlled by its respective anchor node (AN) and denoted by $b_l \in \mathcal{B}$, are deployed at a fixed known geographic position. Each AP is physically mesh-connected to all edge servers. Furthermore, the edge servers are connected to a centralized cloud server and have limited radio resources, denoted by W_l hertz. We consider an open-loop communication where the ANs have perfect channel state information (CSI). Moreover, our software-defined system model is based on [180], where ANs can form and schedule the beamforming weights based on requirements.

By creating a virtual cell for each scheduled user, we aim to guarantee a minimum reliability threshold of the network. Each virtual cell contains multiple APs to serve the respective VU. This process of virtual cell creation is shown by the dotted ellipses in Fig. 104. We denote a user and an AP by $u_i \in \mathcal{U}$ and $a_j \in \mathcal{A}$, respectively, throughout this paper. Furthermore, the VU-AP associations are denoted by the following two indicator functions:

$$a_i^j(t) = \begin{cases} 1, & \text{if AP } a_j \text{ is associated with VU } u_i \\ 0, & \text{otherwise.} \end{cases} \quad (\text{E.1})$$

$$u_j^i(t) = \begin{cases} 1, & \text{if VU } u_i \text{ is associated with AP } a_j \\ 0, & \text{otherwise.} \end{cases} \quad (\text{E.2})$$

Therefore, $\mathcal{A}_i(t)$ denotes the set of APs that VU u_i is connected to and $\mathcal{U}_j(t)$ is the virtual cell for the VU u_i .

¹In this paper, we aim at establishing software-defined edge network architectures for vehicular systems. But, our system model can be easily extended to other practical wireless edge environments.

E.2.2 SD-V2I Communication Model: We consider a multiple-input-single-output communication model. Each VU has a single antenna, whereas each AP has N_j antennas². The wireless channel is considered to be quasi-static flat fading during a basic time block. The channel between VU u_i and the APs are denoted by $\mathbf{h}_i(t) = [\mathbf{h}_{a_1}^T(t), \mathbf{h}_{a_2}^T(t), \dots, \mathbf{h}_{a_A}^T(t)]^T = \mathbf{D}_i(t)\mathbf{p}_i(t)\boldsymbol{\zeta}_i(t) \in \mathbb{C}^{N \times 1}$, where $\mathbf{h}_{a_j}^i(t) = [h_{ij_1}(t), h_{ij_2}(t), \dots, h_{ij_{N_j}}(t)]^T$, $\mathbf{D}_i(t)$, $\mathbf{p}_i(t)$ and $\boldsymbol{\zeta}_i(t) \sim \mathcal{CN}(\mathbf{0}, \mathbf{I}_N)$ are the channel response at a VU u_i from the AP a_j , large scale fading, log-Normal shadowing and fast fading channel vectors, respectively. Furthermore, the beamforming vector for VU u_i is denoted by $\mathbf{w}_i(t) \triangleq [\mathbf{w}_{a_1}^T(t), \dots, \mathbf{w}_{a_A}^T(t)]^T \in \mathbb{C}^{N_i \times 1}$, where $\mathbf{w}_{a_j}^i(t) \in \mathbb{C}^{N_j \times 1}$ represents the beamforming vector of AP a_j for VU u_i at time t . Using this beamforming vector, the transmitted signal of AP a_j is denoted as $\mathbf{s}_j(t) = \sum_{i=1}^U \mathbf{w}_{a_j}^i(t)x_i(t)$, where $x_i(t)$ is the unit powered signal for u_i and $\mathbb{E}[x_i^H(t)x_i(t)] = 1$. As such, at time t , the downlink received signal at u_i is calculated as follows:

$$\begin{aligned} y_i(t) &= \sum_{a_j \in \mathcal{A}} \mathbf{h}_{a_j}^H(t) \mathbf{s}_j(t) + \eta_i(t) \\ &= \mathbf{h}_i^H(t) \mathbf{w}_i(t) x_i(t) + \sum_{u_{i'} \in \mathcal{U} \setminus u_i} \mathbf{h}_i^H(t) \mathbf{w}_{i'}(t) x_{i'}(t) + \eta_i(t) \end{aligned} \quad (\text{E.3})$$

where $\eta_i(t)$ is the received noise at time t . Besides, $\eta_i(t)$ is circularly symmetric complex Gaussian distributed with zero mean and σ^2 variance.

E.2.3 User-Centric Dynamic Cell Formation: The vehicular edge network is considered to operate in time division duplex mode. Thus, we calculate the achievable rate for VU u_i , at time t , as follows:

$$R_i^t(\mathbf{W}(t)) = (1 - \kappa) \log_2 \left(1 + \frac{|\mathbf{h}_i^H(t) \mathbf{w}_i(t)|^2}{\sigma^2 + \sum_{u_{i'} \in \mathcal{U} \setminus u_i} |\mathbf{h}_i^H(t) \mathbf{w}_{i'}(t)|^2} \right), \quad (\text{E.4})$$

where κ is spectral efficiency loss due to signaling at the APs and $|\mathbf{h}_i^H(t) \mathbf{w}_i(t)|^2 / (\sigma^2 + \sum_{u_{i'} \in \mathcal{U} \setminus u_i} |\mathbf{h}_i^H(t) \mathbf{w}_{i'}(t)|^2) = \gamma_i^t(\mathbf{W}(t))$ is the SINR. Moreover, as multiple APs are scheduled to transmit to u_i , the backhaul link consumption by the VU is carefully calculated as follows [66]:

$$C_i(t) = \left\| \left[\left\| \mathbf{w}_{a_1}^i(t) \right\|_2, \dots, \left\| \mathbf{w}_{a_A}^i(t) \right\|_2 \right] \right\|_0 R_i^t(\mathbf{W}(t)), \quad (\text{E.5})$$

where $\|\cdot\|_0$ denotes the total number of nonzero elements in a vector. This is commonly known as the l_0 -norm. If a user is scheduled in a transmission time slot t , the precoding vectors from all of the APs for that VU, i.e., $\mathbf{w}_i(t)$, is nonzero leading to a nonzero achievable data rate.

Note that we presume to serve all active users, in a transmission time slot, by forming virtual cells for each user and dynamically allocating transmission power of the APs. As such, we intend to find optimal user-centric cell formation and beamforming weights calculation - for the APs, in our objective function. The first question that we try to answer is - *what is the maximum throughput in our SD controlled highly mobile vehicular network?* A naive approach would be serving a user from as many APs as possible with the maximum transmission powers of the APs. However, this will bring down the user fairness and EE whatsoever. Therefore, it is essential to justify the user data rate with EE. To avoid cross-domain nomenclature, let us define what we refer to as the EE. *The fraction of the total user sum rate to the total power consumption of the network is defined as EE.* At a given time slot t , we calculate EE as follows:

$$EE(t) = \frac{\sum_{u_i \in \mathcal{U}} C_i(t)}{\sum_{a_j \in \mathcal{A}} \sum_{u_i \in \mathcal{U}} \left\| \mathbf{w}_{a_j}^i(t) \right\|_2^2}, \quad (\text{E.6})$$

where $C_i(t)$ is calculated in Equation (E.5).

Therefore, in this paper, we address the following question: *what are the user-centric associations and power allocations that guarantee reliability, programmability, and EE of the entire network?* To this end, we formulate a

²While we consider omnidirectional antennas in this paper, the proposed framework can easily be extended with directional antennas and beam patterns to further improve SINR at vehicle receivers.

joint optimization problem as follows:

$$\begin{aligned} \textbf{Find:} \quad & a_i^j(t), u_j^i(t), \mathbf{w}_{a_j^i}(t), \quad \forall i \in \mathcal{U}, j \in \mathcal{A} \\ \textbf{Maximize} \quad & EE(t) \end{aligned} \tag{E.7a}$$

$$\textbf{Subject to} \quad 1 \leq |\mathcal{A}_{ij}(t)| \leq A, \quad \forall i \in \mathcal{U} \tag{E.7b}$$

$$\gamma_i'(\mathbf{W}(t)) \geq \gamma_i^{\min}, \quad \forall i \in \mathcal{U} \tag{E.7c}$$

$$\sum_{i=1}^U \left\| \mathbf{w}_{a_j^i}(t) \right\|_2^2 \leq P_j^{\max}, \quad \forall j \in \mathcal{A} \tag{E.7d}$$

$$a_i^j(t) \in \{0, 1\}, u_j^i(t) \in \{0, 1\}, \tag{E.7e}$$

where $\gamma_i^{\min}$ is the minimum SINR requirement for our reliable communication. The reliability constraint is reflected in equation (E.7c). $P_j^{\max}$ is the maximum allowable transmit power of AP a_j which is controlled via equation (E.7d). Equation (E.7b) is taken to ensure each virtual cell contains more than one APs. Moreover, Equation (E.7e) indicates the feasible solution space. Note that the l_0 norm restricts using the gradient-based solution. Besides, the formulated problem is a hard-combinatorial problem, which is extremely difficult to solve within a short period. Moreover, for each of the AP, at each time slot t , there are $2^U - 1$ possible combinations only for the possible VU-AP associations. For each of these associations, the AP, furthermore, needs to choose the optimal power level for the scheduled users. Note that, in this paper, instead of a continuous power level, we divide the AP's transmission power level into multiple discrete levels. As our SD controlled ANs know the perfect CSI, we model the beamforming vector as follows:

$$\mathbf{w}_{a_j^i}(t) = \frac{\mathbf{h}_{a_j^i}(t)}{\left\| \mathbf{h}_{a_j^i}(t) \right\|_2} \times \sqrt{P_{a_j^i}(t)}, \tag{E.8}$$

where $\mathbf{h}_{a_j^i}(t)$ is the wireless channel information from AP a_j to VU u_i and $P_{a_j^i}(t)$ is the allocated transmission power of AP a_j to transmit to VU u_i . If a centralized decision has to be taken, the centralized agent needs to make a central decision for all of the AP-VU associations and their power level selections. In that case, the size of the action space is $O((2^U - 1)^A \times K^{UA})$, where K is the total discrete power levels. Thus, traditional optimization methods may take an enormous amount of time to solve such an intricate problem. As such, we use a model-free Q -learning approach to solve the optimization problem efficiently in the next section.

E.3 Energy-Efficient Resource Slicing at Edges: A Reinforcement Learning Approach

As we assume the CSI is known, our state-space contains all CSIs - denoted by $\mathbf{H}^t$, the locations of the VUs - denoted by $\mathbf{X}_i^t$, and the locations of the APs - denoted by $\mathbf{X}_j^t$. Therefore, we denote the state-space by $\mathbf{s}_t = \{\mathbf{X}_i^t, \mathbf{X}_j^t, \mathbf{H}^t\}$. On the other hand, the action space contains the VU-AP association and beamforming vectors for the chosen association. The action space is, thus, a two-step process. First, the RL agent needs to choose a possible association. After that, it designs the beamforming vectors. We express the action space as $\mathbf{a}_t = \{a_j^i(t) \mid \forall i \in \mathcal{U}, P_{a_j^i}(t) \mid \forall i \in \mathcal{U} \& j \in \mathcal{A}\}$. Moreover, we have taken the EE in Equation (E.6) as the reward function of the RL agent. However, to ensure fairness among users achievable rate and reliable communication, at each time slot t , we have employed the following restriction:

$$r_t = \begin{cases} EE(t), & \text{if } \gamma_i'(\mathbf{W}(t)) > \gamma_i^{\min} \quad \forall u_i \in \mathcal{U} \\ 0, & \text{otherwise.} \end{cases} \tag{E.9}$$

E.3.1 Single Agent Reinforcement Learning (SARL): Taking the state-space and action-space into account, Q -learning based RL framework can effectively solve hard optimization problems. Note that it is a model-free learning [181, 329] process, where in each state $\mathbf{s}_t$, the agent takes an action $\mathbf{a}_t$, gets a reward r_t for the chosen action and the environment transits to the next state $\mathbf{s}_{t+1}$. The governing equation of Q -learning is shown in the following:

$$Q(s_t, a_t) \leftarrow (1 - \alpha)Q(s_t, a_t) + \alpha \left(r_t + \gamma \max_{\mathbf{a}} Q(s_{t+1}, \mathbf{a}) \right), \tag{E.10}$$

where α and γ are learning rate and discount factor, respectively. Although SARL is a good baseline scheme, if the number of states and actions is too large, it may become impracticable to handle. For example, if $U = A = 3$ and $K = 4$, then the baseline centralized SARL has an action space³ of order $O((2^U - 1)^A \times K^{UA}) = 89915392$. This is commonly known as the curse of dimensionality. Please note that, in a learning environment, if the number of states is infinite, usually we approximate the state using some means of approximation [292], such as linear approximation, neural network, etc. However, the number of action remains unchanged. For each approximated state, the learning agent still must take action from the original large action-space [292]. As an alternative, we propose a D-MARL solution in what follows.

E.3.2 Distributed Multi-Agent RL (D-MARL): The fundamental assumption in traditional MARL is allowing multiple agents to take their independent decisions so that we have a shrunk action-space for each agent. Then, the idea is to collaboratively learn a joint action set such that optimal network performance can be achieved. Although the action space for each agent is small compared to that of the centralized SARL⁴, whether MARL will accomplish the optimal solution within reasonable training episodes is uncertain as all learning agents need to reach to a consensus cooperatively for maximizing the reward. Therefore, we have used the concept of MARL. Yet, instead of letting multiple-agents taking independent actions from a shrunk action space, we have used a distributed learning process where each agent takes decisions from a segmented original SARL's action space. In other words, the original SARL's action space is subdivided into multiple groups. Each agent takes its decision from an assigned smaller group.

If there are N such agents, then the dimension of the Q -table of such an agent is $\mathbb{R}^{S \times A/N}$, where S and A represents the size of the state space and action space, respectively. Therefore, the order of the action space of each agent is of $O(\Phi)$, where $\Phi = [(2^U - 1)^A \times K^{UA}] / N$. Furthermore, let us assume there is a centralized vector - denoted by $\mathbf{Q}_{central} \in \mathbb{R}^S$, that stores the global best action at every state. We update this global best action using the following equation:

$$\mathbf{Q}_{central}[\mathbf{a}_t] \leftarrow \begin{cases} \mathbf{Q}_{central}[\mathbf{a}_t], & \text{if any } r_t[\mathbf{a}_t] > r_t[\mathbf{a}_t^{old}], \forall \text{ agents } \in N \\ \mathbf{Q}_{central}[\mathbf{a}_t^{old}], & \text{otherwise.} \end{cases} \quad (\text{E.11})$$

Therefore, our proposed D-MARL solution distributively learns to take the optimal central action quickly. On the other hand, traditional MARL [186, 340] may not achieve the optimal solution, as independent agents take autonomous actions in a shrunk action space, within a reasonable time. The joint actions of these agents may not be centrally optimal and lead to a sub-optimal solution. Algorithm 4 summarizes our proposed D-MARL solution.

Algorithm 4: Distributed Multi-Agent RL (D-MARL)

- 1: **Initialize:** Total number of agents, N {Choose N so that $\text{Actions}/N \in \mathbb{Z}^+$ }
 - 2: Generate random $\mathbf{Q}_l(\mathbf{s}_t, \mathbf{a}_t)$ tables, where $l \in N$.
 - 3: Generate $\mathbf{Q}_{central} \in \mathbb{R}^S$ randomly
 - 4: **for each episode do**
 - 5: Initiate the environment, generate $\mathbf{s}_t = \{\mathbf{X}_i^t, \mathbf{X}_j^t, \mathbf{H}^t\}$
 - 6: **while not terminated do**
 - 7: **for each** $l \in N$ **do**
 - 8: Observe the environment; choose $\mathbf{a}_t$, based on the observation, following ϵ -greedy policy; receive reward r_t ; update its Q -table using equation (E.10)
 - 9: **if** $r_t > \text{reward using } \mathbf{Q}_{central}[\mathbf{a}_t]$ **then**
 - 10: update $\mathbf{Q}_{central}$ using equation (E.11)
 - 11: $\mathbf{s}_t \leftarrow \mathbf{s}_{t+1}$ {If $\mathbf{s}_t$ is the terminal state}
-

³Note that this contains the total action space. The number of valid actions will be lesser than this due to the maximum allowable transmission power constraint of the AP.

⁴For the same example of the centralized SARL one, if we consider each AP as an independent agent for the MARL scheme, the order of the action space for an agent is $O((2^U - 1) \times K^U) = 448$.

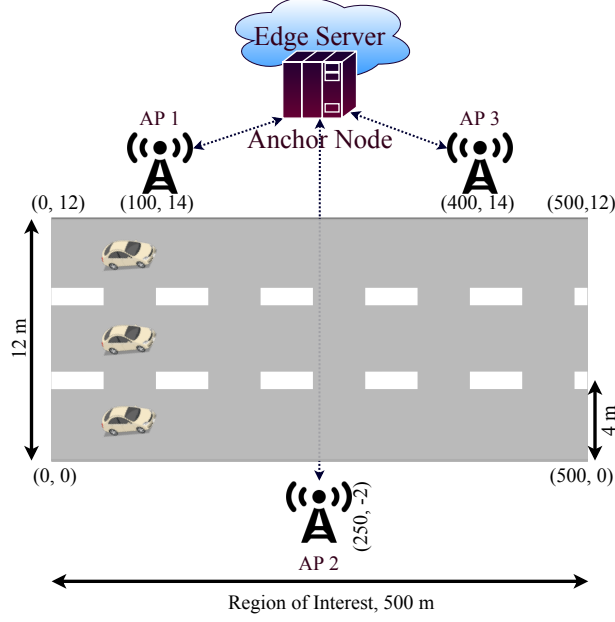


Figure 105. Simulation environment

Table 47. Performance Comparisons: $\gamma_i^{min} = 10$ dB, AP Coverage Radius = 250 m

Scheme Name	Training Episodes	Test Episodes	Average EE [bits/Hz/J]	Deviation from Benchmark
Brute Force (Benchmark)	N/A	250	2.319512196	0% (Benchmark)
D-MARL (Proposed)	25000	250	2.319498972	0.0005%
SARL [181]	100000	250	2.319509675	0.0001%
MARL [340]	100000	250	2.289516849	1.2932%
Equal Power	N/A	250	0.002361365	99.8982%
Random Power	N/A	250	0.038780234	98.3281%

E.4 Performance Evaluation

We consider ROI = 500 m, VU velocity = 140 km/h, $|\mathcal{U}| = |\mathcal{A}| = 3$, $|\mathcal{B}| = 1$, 8 antenna per AP, noise power = -114 dBm/Hz, and $\kappa = 0.1$. The channels, path loss, and shadowing are modeled following [3]. For the ease of simulation, we consider a full buffer network model where all APs serve all VUs simultaneously. We consider the following association rule:

$$a_j^i(t) = \begin{cases} 1, & \text{if } u_i \text{ is in the coverage region of AP } a_j \\ 0, & \text{otherwise.} \end{cases} \quad (\text{E.12})$$

Note that our proposed problem solution can work in other scheduling algorithms as well. While the VUs are dropped uniformly in each lane, the APs are placed 150 meters apart fixed locations. For a tractable state space, we have considered that, at a given time step, all VUs are in the same x locations - while they have different y locations. The simulation setup is presented in Fig. 105. Here we stress out that while we consider a restricted simplified version of the environment for our simulation, our proposed algorithm shall achieve similar performances in a more comprehensive platform. To show the effectiveness of our proposed solution, we compare its performances to the optimal benchmark performance. We apply certain restrictions only due to limited computation resource availability.

E.4.1 Average Energy-Efficiency Comparisons To this end, we show the effectiveness of the proposed D-MARL algorithm. Specifically, we compare our design with the following schemes:

- *Brute Force (Benchmark)*: This is the optimal solution. In this case, at each state, we need to search for the optimal action that provides the maximum reward.
- *SARL [181]*: This is the baseline RL scheme. We adopted the learning process in [181] for this case. Note that this is a centralized learning process. In this case, the RL agent has a large action-space. Such a centralized learning agent shall take a sufficiently large number of training episodes to reach the optimal solution.

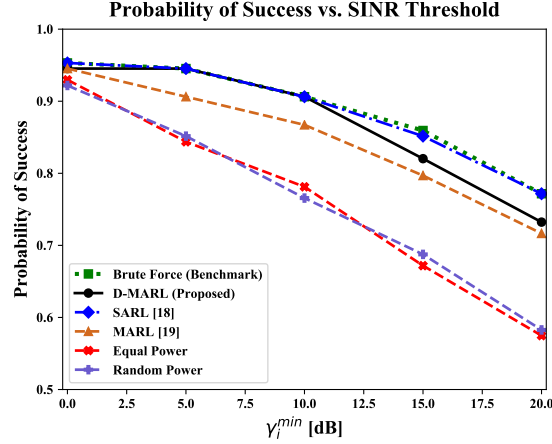


Figure 106. Probability of success for different SINR threshold when AP coverage radius is 250 m

- *MARL [340]*: We have used the novel cooperative MARL learning process proposed by Yao *et al.* in [340]. Note that a similar approach is also considered by Liu *et al.* in [186]. Here we stress out that while there exist other MARL models, we used recently proposed collaborative learning approaches of [340] and [186] for our performance comparison. We intend to validate that the proposed D-MARL algorithm delivers near-optimal performances within a nominal number of training episodes.
- *Equal Power Allocation*: In this case, we have assumed that the AP divides its transmission power equally to serve the VUs. Essentially, this is the centralized case where the central power allocation decision is chosen in such a way that each AP transmits to its scheduled users using equal power.
- *Random Power Allocation*: We have assumed that the AP chooses random transmission power from the discrete power level to serve a VU. This is also a centralized case in which, at each state and time slot, we choose a random central decision from the possible centralized action space.

We use each AP as an independent agent for the MARL algorithm. Therefore, there are three agents for MARL [340], where each AP takes its association and power allocation decision independently. For our proposed D-MARL algorithm, we have used four agents. The SARL and MARL models are trained on 1×10^5 episodes, whereas the D-MARL model is trained only on 25×10^3 episodes. We have taken $\gamma = 0.8$. The values of both ϵ and α are decayed linearly from 1 to 0.01 in each episode. From 250 test episodes, the performance comparisons of our proposed algorithm with other schemes are listed in Table 47. Note that we have taken $\gamma_i^{\min} = 10$ dB and AP coverage radius = 250 m for this comparison. Clearly, machine learning solutions achieve much higher performances than two baseline schemes (equal power allocation and random power allocation). Furthermore, thanks to RL, the centralized baseline SARL solution and the proposed D-MARL solution deliver nearly identical performance to that of the brute force optimal performance. The agents learn to take optimal actions from the training episodes and deliver a near-optimal performance. The performance of the MARL [340] is also very close to this optimal solution. However, recall that SARL and MARL models are trained on four times the training episodes used in our proposed D-MARL algorithm. These results also substantiate that a distributed learning choice on the centralized action-space is beneficial over learning on a shrunk action-space as in [186, 340]. Furthermore, our proposed D-MARL solution achieves ≈ 29 dB and ≈ 18 dB performance gain over equal power allocation and random power allocation schemes, respectively.

E.4.2 Impact of the Reliability Constraint: The reliability constraint has a significant impact on the overall network performance. If we increase the reliability constraint, $\gamma_i^{\min}$, we force the RL agents to find optimal solutions that maximize the EE without violating the reliability constraint. Therefore, as this constraint increases, the number of total failed events also increases. First, let us calculate the success probability of achieving the reliability constraint as follows:

$$\Pr \{\text{success}\} = 1 - \frac{1}{T} \sum_{t \in T} I_f(t), \quad (\text{E.13})$$

where T is the total number of time steps and $I_f(t)$ is an indicator function for the event that $\gamma'_i(\mathbf{W}) < \gamma_i^{\min}$ for any of the $u_i \in \mathcal{U}$. The probability of delivering the minimum required SINR is shown in Fig. 106. The RL algorithms perform better than the baseline schemes. Furthermore, as $\gamma_i^{\min}$ increases, the successful transmission events get

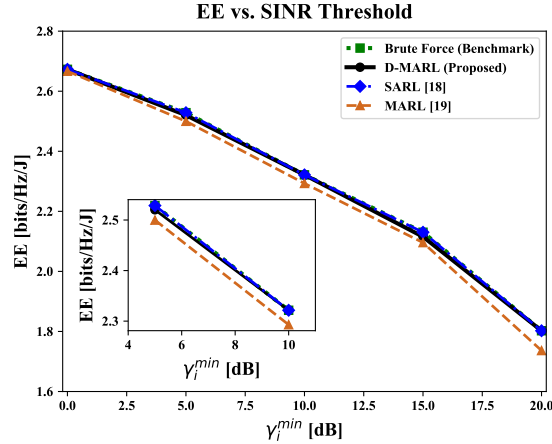


Figure 107. Average EE for different SINR threshold when AP coverage radius is 250 m

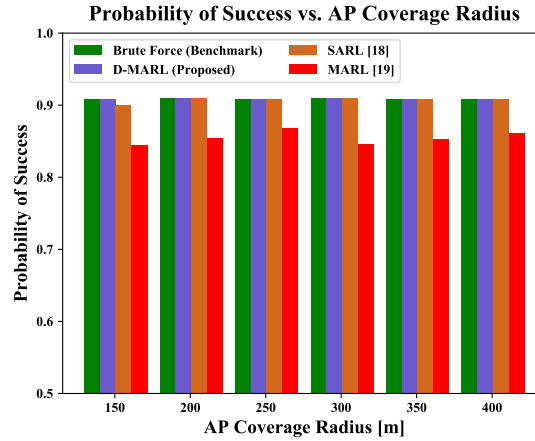


Figure 108. Probability of success for different AP coverage radius when SINR threshold is 10 dB decayed. Note that our proposed D-MARL can deliver near-optimal success probability with these varying reliability requirements. On the other hand, the performance gap between MARL [340] and D-MARL is quite evident from this result. Moreover, increasing the reliability constraint may necessitate the APs to transmit to the VUs with more power - so that it can attain the SINR threshold. However, this downgrades the EE. Our simulation results in Fig. 107 also reflects this. As the performances of the two baseline schemes (equal power allocation and random power allocation) are very poor compared to the RL schemes, hereinafter, we will only compare the performance of our proposed algorithm with the brute force (benchmark) and other two RL schemes.

E.4.3 Impact of the Coverage Radius: Now, we analyze the impact of the coverage radius of the APs by keeping the reliability constraint fixed and varying the coverage radius. Note that as the reliability constraint is fixed, the probability of success, as shown in Equation (E.13), should not fluctuate rapidly if the coverage radius is varied. This is also reflected in Fig. 108. Besides, as the coverage radius of the AP increases, more VUs can be served by each of the APs. Although the SINR constraint is fixed, recall that from our association rule in Equation (E.12) and rate calculation in Equation (E.5), it is quite clear that increasing the coverage radius will increase the total number of links for a VU. This will, therefore, improve the user sum rate. On the other hand, if the VU is far away from an AP, the AP might need to transmit to it with more power. However, the RL agents will find optimal power allocations to increase the user sum-rate that ultimately increases the EE in Equation (E.6). This trend is also reflected in our simulation results in Fig. 109. As the coverage radius increases, the D-MARL algorithm finds optimal associations and power allocations, leading to an improved EE of the network.

E.4.4 User Fairness: Furthermore, a reliable and efficient network should ensure fairness while serving its associated users. A fair system delivers a nearly equal data rate to all users. Notice that our reward function, in Equation (E.9), designed such a way that it delivers a zero reward if any VU's downlink SINR is below the threshold level. Therefore, the proposed solution guarantees a minimum data rate for all users. Besides, since this threshold is

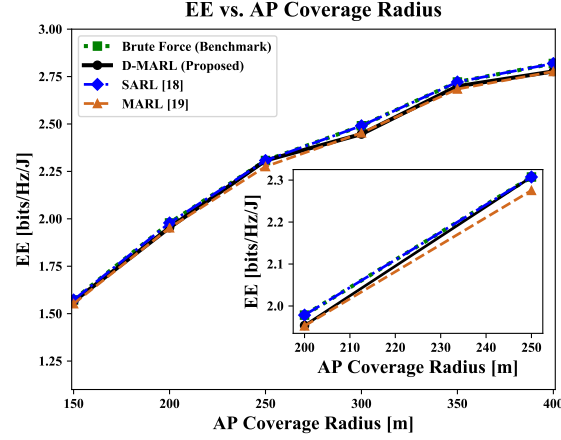


Figure 109. Average EE for different AP coverage radius when SINR threshold is 10 dB

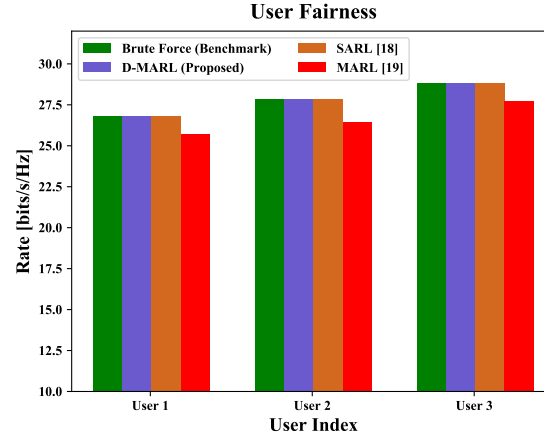


Figure 110. User fairness: AP coverage radius 250, SINR threshold 10 dB

equal for all VUs, each of them shall receive a nearly identical data rate. From 250 test episodes, user fairness - while conserving the maximized EE, is presented in Fig. 110. Our proposed D-MARL delivers a Jain's fairness index [137] $\left(\frac{(\sum_{u_i \in \mathcal{U}} C_i(t))^2}{|\mathcal{U}| \sum_{u_i \in \mathcal{U}} C_i(t)^2} \right)$ of ≈ 0.99915 . The fairness index for the optimal scheme, SARL [181] and MARL [340] are 0.99915, 0.99915, and 0.99899, respectively. Note that this fairness index varies between 0 and 1. A fairness index of 0 means there is no fairness whatsoever in the network. Fairness among users increases with the rise of this index.

E.5 Conclusion

In this paper, we have jointly optimized virtual cell formation and power allocation to assure ubiquitous connectivity and reliability at the vehicular edge networks for connected transportation. Thanks to RL's powerful complex problem-solving ability, the hard combinatorial joint optimization problem is efficiently solved using this sophisticated learning process. While we exploited several RL models, we conclude that a distributed learning approach on the centralized action-space delivers better performance over the traditional collaborative MARL model. Especially, our proposed sophisticated D-MARL solution attains near-optimal benchmark performance within a nominal number of training episodes.

APPENDIX: F.6
CAV Revenue Impact Analysis and Mitigation strategies

Appendix F CAV Revenue Impact Analysis and Mitigation Strategies

F.1 Introduction

NCDOT's revenue portfolio is heavily reliant on the taxation of motor fuels. Approximately 42 percent of its revenue comes from the state Motor Fuels Tax, while the next largest source at 23 percent, Federal funding, is itself largely derived from Federal fuel taxes [55] (Fig. 111). Furthermore, a majority of the remaining funding relies on the personal ownership and operation of motor vehicles. As a result, the adoption of connected and autonomous vehicles poses a major threat to the financial sustainability of North Carolina's transportation system. As CAVs are adopted, NCDOT's revenues face strong downward pressures from challenges such as electrification, improving fuel economy, and a shift away from driving and personal vehicle ownership.

F.1.1 Current revenue sources

F.1.1.1 Motor Fuels Tax A fuel tax is an excise tax imposed on the sale of fuel. In most countries, a fuel tax is imposed on fuels that are intended for transportation, while fuels used to power agricultural vehicles and/or home heating oil, which is similar to diesel, are usually taxed at a different, usually lower rate. In the United States, every state imposes its own tax on gasoline in addition to one charged nationwide by the Federal government. North Carolina charges a per US gallon tax on the purchase of motor fuels. Currently, as of 2023, the rate on both gasoline and diesel is \$0.405 per US gallon, excluding a \$0.0025 per gallon inspection tax [222]¹. In the state fiscal year (SFY) 2020, North Carolina Motor Fuels Tax revenue totaled \$1.9 billion [56]).

F.1.1.2 Federal Funding 23% of NCDOT's total revenue from Federal funding sources [55]. The primary source of Federal funds are excise taxes charged on gasoline and diesel sales of \$0.183 and \$0.243 per US gallon [83]².

Funds raised from this excise tax are dedicated to the Highway Trust Fund, with \$0.0286 per gallon directed towards the Mass Transit Account and the remainder directed towards the Highway Account [93].

This funding source faces similar pressures as North Carolina's Motor Fuels Tax due to increasing fleetwide fuel economy and changing driving patterns. Furthermore, these rates were last adjusted in 1993, meaning that in real terms they have fallen by over half over the intervening three decades [236]. Fig. 112 shows the loss in real purchasing power due to the Federal gasoline tax remaining at 18.4 cents per gallon since 1993: it has lost over 50 percent of its purchasing power due to inflation. According to estimates from the Bureau of Labor Statistics [236], approximately 38.4 cents in November 2022 is equivalent to 18.4 cents in 1993.

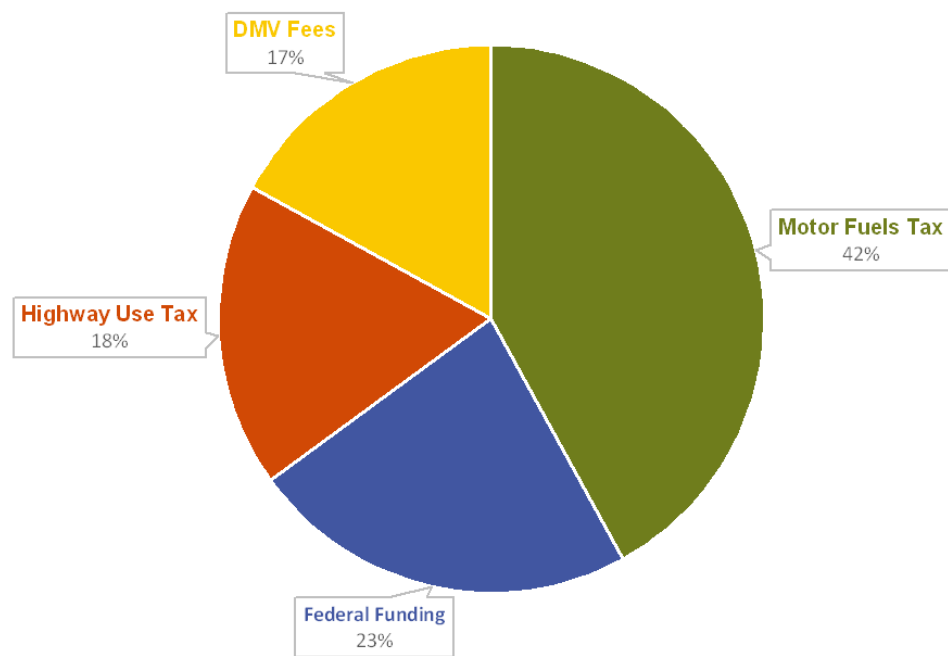
Additional sources of funding for the Highway Trust Fund include taxes on special fuels and truck-specific taxes on tires, sales and heavy vehicle use (charged annually), all of which are solely dedicated to the Highway Account [93]. Federal funding is restricted and cannot be used freely for any project or even any road; in fact, only 28 percent of North Carolina's state highway road miles can possibly receive such funds [55].

F.1.1.3 Highway Use Tax In 1989, North Carolina switched from a sales tax on vehicle purchases to the Highway Use Tax (HUT). A primary motivation for this change was direct revenues associated with vehicle purchases into North Carolina's Highway Trust Fund. Today, whenever a vehicle title is transferred in North Carolina, the buyer is charged a one-time, 3 percent tax on the vehicle's purchase price, less any trade-in value if the vehicle was purchased at a dealership [57]. North Carolina's HUT functions similarly to a vehicle sales tax or a sales and uses tax, which is the mechanism predominantly used in other states to direct sales tax revenue from vehicle sales into a transportation fund. Some states impose vehicle-specific taxes in lieu of a state sales tax, while other states direct a portion of their vehicle sales tax revenue into transportation accounts.

F.1.1.4 Alternative Highway Use Tax When a vehicle is leased or rented rather than sold, North Carolina charges an Alternative Highway Use Tax (AHUT) in lieu of the standard HUT. Long-term leases and rentals are charged a rate of 3%, which is deposited in the Highway Trust Fund. Short-term rentals and leases are charged a rate of 8% and vehicle subscription services are charged an intermediate rate of 5%; however, only a portion of the AHUT

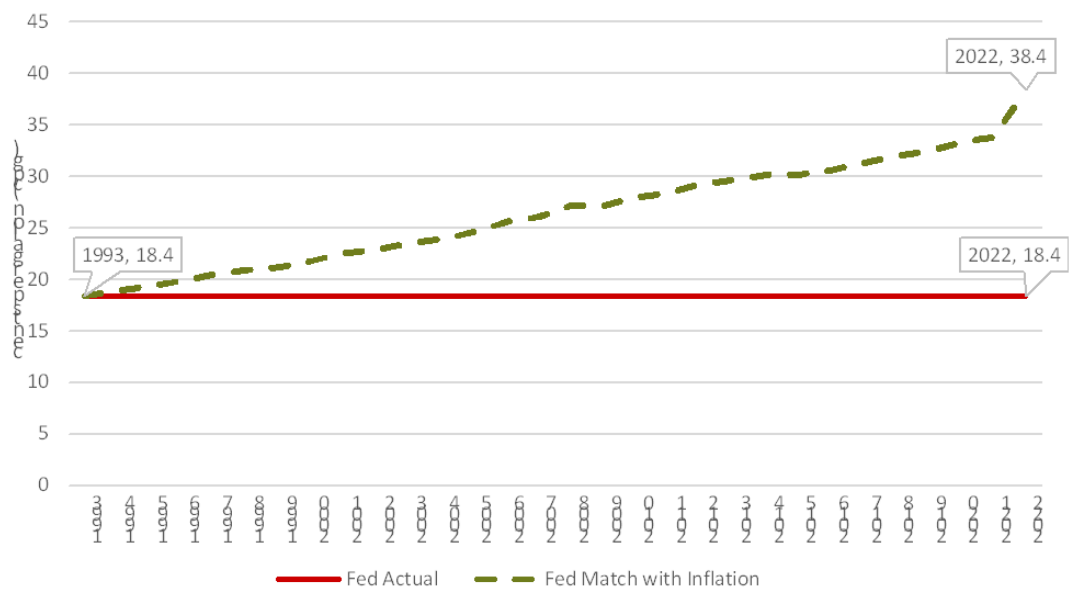
¹The NCDOR website incorrectly states that the inspection tax is ".0025 cents per gallon" [222]. It is, in fact, "one-fourth of one cent (1/4 of 1¢) per gallon", which is \$0.0025 or 0.25¢ per gallon

²An additional \$0.001 is charged per US gallon both to fund underground storage tank cleanup, making the effective rates \$0.184 and \$0.244 per US gallon respectively.



Source: (NC FIRST Commission, 2021, p. 30)

Figure 111. Current NCDOT funding sources



Sources: Authors' illustration; (US Energy Information Administration (EIA), 2022), (US Bureau of Labor Statistics (BLS), 2022)

Figure 112. Federal gasoline tax vs CPI inflation, 1993-present

charged on these is deposited in the Highway Trust Fund, with the rest remitted to the state's General Fund [57].

F.1.1.5 DMV Fees North Carolina uses DMV fees to support a wide variety of uses, most of which are dedicated toward the construction and maintenance of the state's highway network. In 2020, DMV registration fees accounted for approximately 11.4 percent (\$610.3 million) of state transportation revenue, DMV title and other miscellaneous fees accounted for approximately 3.8 percent of revenue (\$201.3 million), and DMV licensing fees accounted for approximately two percent of revenue (\$108.9 million) [223]. Altogether, DMV fees accounted for approximately 17.2 percent of the state's transportation revenue.

F.1.1.6 Supplemental Fee on Electric Vehicles North Carolina motorists pay an annual registration fee of \$36 plus an additional annual fee of \$140.25 for plug-in electric vehicles [286]. Proponents support electric vehicle fees to bring equity among drivers by ensuring all drivers pay for using roadways [130]. Across the nation, 28 states have additional registration fees for electric vehicles similar to North Carolina's, ranging from \$50 to \$213 per year [58].

F.1.1.7 Other Sources A negligible amount of revenue comes from other sources, such as tolling.

Tolling

Since the opening of the Triangle Expressway, North Carolina's first modern toll road, in 2011, the state's network of tolled roads has grown to 64 miles across three facilities:

- The **Triangle Expressway**, an 18.8-mile toll road in Wake and Durham counties
- The **Monroe Expressway**, an 18-mile toll road in Mecklenburg and Union counties
- The **I-77 Express Lanes**, a 27-mile High-Occupancy Toll (HOT) facility in Mecklenburg and Iredell counties, was built and is maintained by infrastructure firm Cintra under a public-private partnership agreement

Two further projects are under construction—an extension of the Triangle Expressway and the addition of HOT lanes to Interstate 485 in southern Mecklenburg County—and, as of December 2022, three other projects are under development [224].

Under current law, the NC Turnpike Authority is required to spend the money raised by its toll facilities on the same toll facility, on a contiguous toll facility, on debt service, or on Authority administration [9].

F.2 Comparing to Other States

North Carolina is more reliant on funding from motor fuel taxes than most other states for maintaining its highway network. This is especially true once Federal funding is removed: According to a Tax Foundation analysis, once Federal funding was excluded, 66% of state highway funding in North Carolina in FY2018 came from motor fuels tax, ranking North Carolina 14th among US states. (The average state sourced only half its highway funding from motor fuels tax.) A comparison of the relative shares of funding by source for NC vs all states is shown in Table 48. Overall, the Tax Foundation analysis found that North Carolina state-sourced revenues were slightly less reliant Table 48. State-sourced highway revenues, FY2018

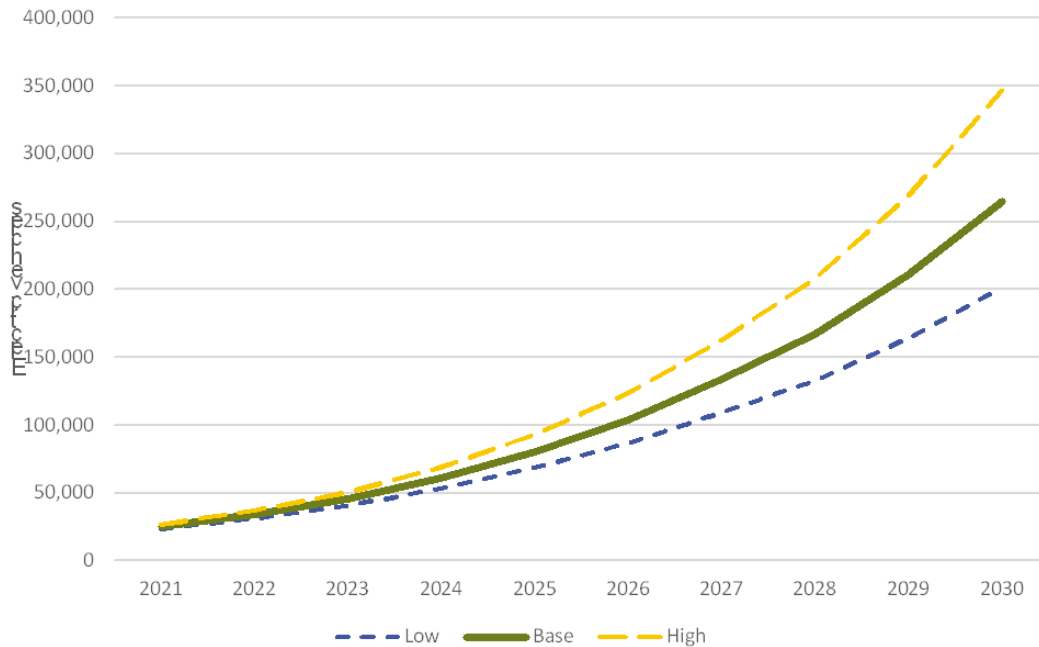
Revenue source	Share among all states	Share in NC	Rank among states
Motor Fuels Tax	49%	66%	14
License revenue	30%	32%	21
Tolls and charges	21%	2%	39

(65 percent) on these user fee sources than the typical (median) state (66 percent)³.

F.3 Revenue challenges

F.3.1 Changing patterns of car usage In the short-term, as technology and the population change, lower overall rates of driving and car ownership are expected [55]. Already, the number of miles traveled per person in North Carolina appears to be leveling off [56]. This could put downward pressure on many of NCDOT's present funding sources. Both lower levels of driving and lower levels of car ownership would pressure the DMV fee and the Highway

³Note that the Highway Use Tax (HUT) is not considered a user fee.



Source: Internal NCDOT forecast from NC ZEV Plan

Figure 113. NC electric vehicle adoption forecast

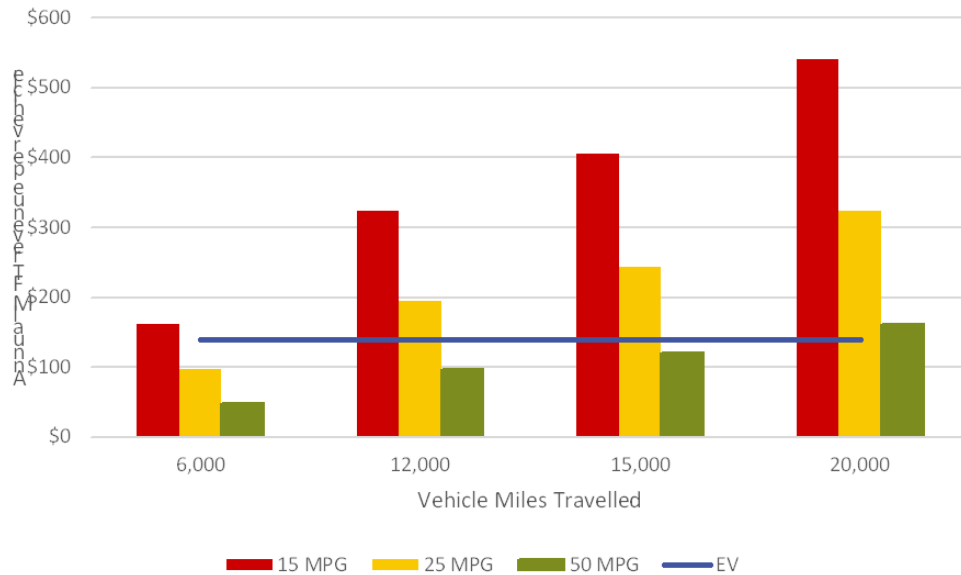
Use Tax revenues (see Decreased fee and HUT revenue below), while decreased driving overall would pressure the Motor Fuels Tax and possibly toll revenues.

However, over a longer time horizon, it is possible that vehicle miles traveled may increase if connected and autonomous vehicles (CAVs) become a significant mode of travel for North Carolinians. CAVs may change the value of time for car usage, lowering the opportunity cost of taking a car and making users willing to travel by car more, rather than less.

F.3.2 Electrification Virtually all CAVs are presumed to be electric vehicles (EVs), and EVs necessitate the use of different tools to raise revenue than the fuel taxes charged to conventionally-powered vehicles. While, as of 2022, electric vehicles make up a small share of the cars on North Carolina roads, that's changing fast. By 2030, over 250,000 vehicles on North Carolina's roads are predicted to be EVs (Fig. 113).

At the moment, North Carolina charges an annual supplemental fee of \$140.25 for electric vehicle registrations to compensate for the revenue lost due to their energy source not being subject to the Motor Fuels Tax. Using DMV data, the NC FIRST Commission found that an EV owner in North Carolina paid \$50 more than the owner of a typical vehicle in 2020 [58]. However, this analysis suffered from a core deficiency: the typical vehicle in North Carolina is not an appropriate comparator. While the typical vehicle in North Carolina as of 2020 was 12.7 years old [58] and had a fuel economy of 22.7 miles per US gallon [56], most EVs on the road are late model and either sedans, hatchbacks or smaller SUVs. Similar late model sedans and SUVs powered by gasoline would also generate much less in Motor Fuels Tax revenue than the average vehicle on North Carolina's road, yet the NC FIRST Commission does not argue that the purchase of a new Toyota Camry results in "Revenue Lost" even though this vehicle too would pay less than the state's average vehicle. (The adverse revenue impacts from the increased efficiency of late-model, conventionally-powered vehicles are discussed further in Improving fuel economy below.)

The North Carolina Clean Energy Technology Center performed a different analysis that instead compared North Carolina's EV fleet to conventionally-powered vehicles of similar age and size and estimates that, as of 2019, the state lost \$100 in Motor Fuels Tax revenue per vehicle; at the time, the EV registration fee was \$130 per year, and therefore electric vehicle owners contributed on average \$30 more per vehicle than owners of comparable vehicles. This meant that electric vehicles then resulted in a net surplus to NCDOT of \$360,000 in total. The Center projects that lost gas tax revenue through 2025 will be between \$103 and \$110 per vehicle [44]. Applying this to the NC ZEV Plan's projections of the size of the state's EV fleet in 2025 results in estimated excess revenue to NCDOT of between



Source: Authors' calculation based on current Motor Fuels Tax and EV registration fee rates

Figure 114. Annual Motor Fuels Tax revenue by VMT as MPG (US) improves \$2.075 million and \$3.475 million⁴.

While electric passenger vehicles currently create a surplus and can be expected to continue to do so in the near future, the adoption of electric heavy vehicles may pose a significant threat: the Clean Energy Technology Center estimated that the lone electric tractor-trailer registered in North Carolina in 2019 may cost the state \$3,800 in lost MFT revenue if it travels a typical number of miles each year [44]. If intercity trucking on limited-access highways proves to be an early application of autonomous technology, then the first CAVs on North Carolina's roads may impose a significant fiscal impact on NCDOT.

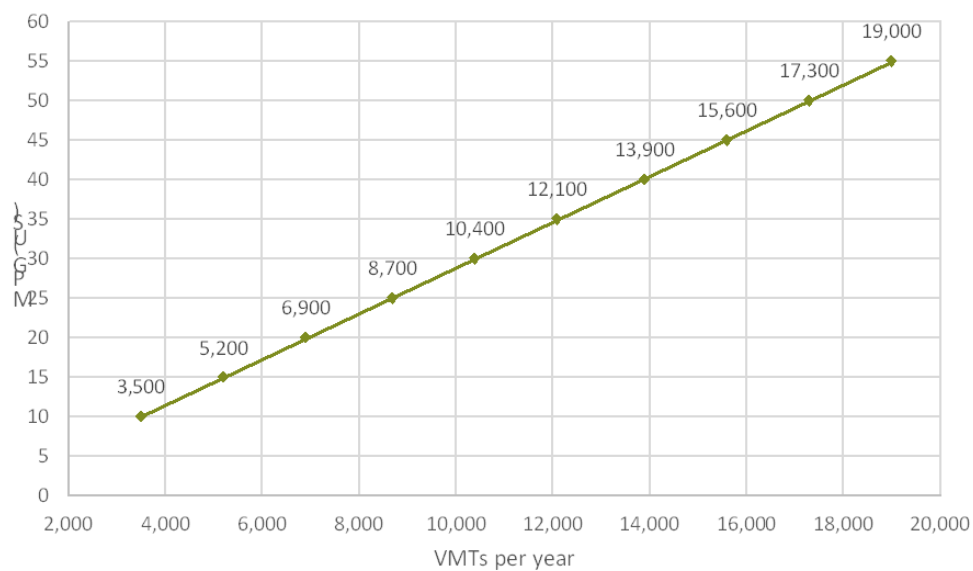
F.4 Decreased fee and HUT revenue

CAV adoption will likely result in a relatively larger share of North Carolinians choosing to go without a driving license, as one would presumably not be needed for their autonomous journeys. This would decrease the revenue that NCDOT generates from driver licensure.

Similarly, it is possible that CAV adoption may cause relatively more North Carolinians to forego car ownership altogether, choosing instead to request on-demand rides from corporately-owned autonomous taxis. This relative shrinking of the overall size of the vehicle fleet would the amount of revenue that NCDOT receives from per-vehicle registration and titling fees. A smaller vehicle fleet may also mean a decrease in the amount of Highway Use Tax (HUT) raised; however, the decrease in HUT from fewer overall vehicles may be offset by the likely higher per-vehicle value of CAVs.

F.4.1 Improving fuel economy It is important to note that in the short term, the largest threat to NCDOT's finances comes not from the adoption of CAVs (or other alternative fuel vehicles) but from improving fuel economy. Small nominal changes in fuel economy for the least efficient vehicles have an outsized effect on fuel consumption and, therefore, on NCDOT's revenues. As seen in Figure 6, at the current MFT rate of \$0.405 per US gallon, replacing a vehicle with a fuel efficiency of 15 MPG (US) that travels 15,000 miles in North Carolina each year with one with a fuel efficiency of 20 MPG (US) decreases NCDOT's revenues by over \$100, while replacing a 35 MPG vehicle traveling that same distance with a 40 MPG one would reduce NCDOT's revenue by less than \$25. In summary, a 5 MPG improvement would cause more than four times the MFT revenue loss at 15 MPG compared to 35 MPG.

⁴\$2.075 million in surplus EV revenue assumes NC ZEV's "low" scenario of 68,600 EVs in 2025, an EV registration fee of \$140.25 and lost MFT per vehicle of \$110; \$3.475 million in surplus EV revenue assumes NC ZEV's "high" scenario of 93,217 EVs in 2025 and lost MFT per vehicle of \$103.



Source: Authors' calculation based on current Motor Fuels Tax and EV registration fee rates

Figure 115. Breakeven analysis: Current electric vehicle fee vs MFT revenue

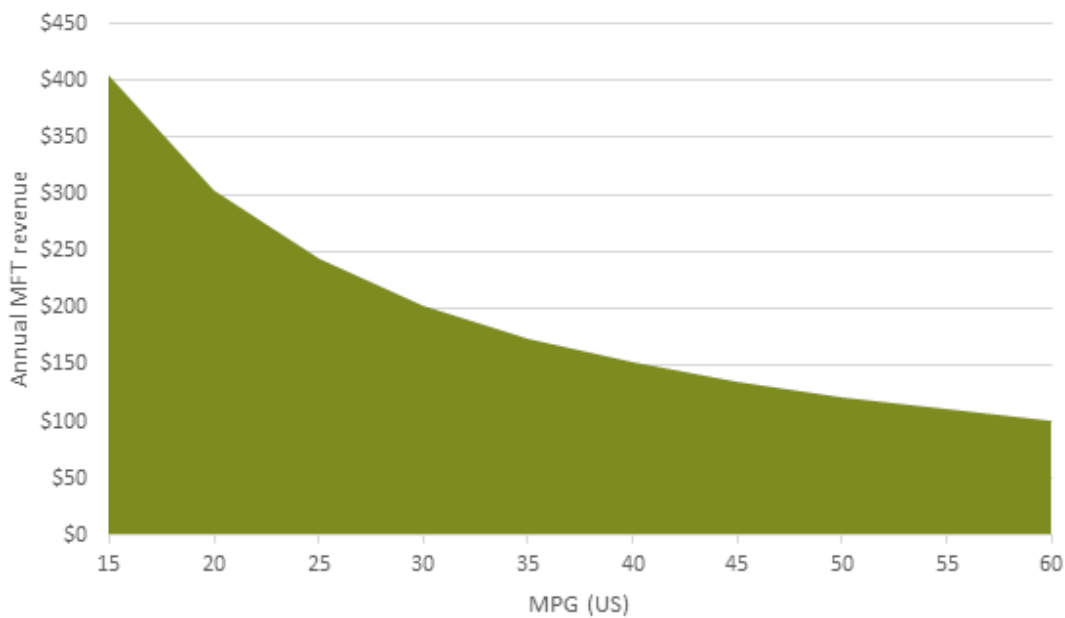


Figure 116. MFT revenue at 15,000 VMTs per year as MPG improves

This effect is more clearly seen when the fuel economies are stated in gallons per 100 miles, rather than miles per gallon. A vehicle with a fuel economy of 10 mpg consumes 10 gallons per 100 miles while one with 15 mpg consumes 6.6 gallons per 100 miles; a vehicle with a fuel economy of 25 miles per gallon consumes 4 gallons per 100 miles, while one with 50 mpg consumes 2 gallons per 100 miles.

In 2010, the average vehicle in North Carolina had a fuel economy of around 20.5 mpg. Between 2010 and 2020, the fuel economy of North Carolina's vehicle fleet improved by 2.4 mpg, resulting in a figure that was by the end of that decade almost 23 mpg [56]. For the typical vehicle, this has already resulted in a decreased consumption of almost 64 gallons per year, representing a reduction in Motor Fuels Tax revenue of about \$23 per vehicle (as well as a reduction in Federal gas tax revenue of about \$9).

These improvements are only expected to continue: by 2026, new cars are predicted to have an average fuel economy of 47.7 mpg and new light trucks 34.1 mpg [55]⁵. The revenue challenge this poses to NCDOT greatly exceeds that of CAVs in any reasonably forecastable time horizon.

F.5 Revenue options

A variety of options are available to address any potential revenue shortfall due to the transition to CAVs, including reforms to existing funding sources as well as entirely new mechanisms. All, however, have trade-offs that need to be fully explored and considered before implementing changes to the current funding paradigm.

F.5.1 Implementation of a Road User Charge A road user charge (RUC), also frequently referred to as a vehicle miles traveled (VMT) tax, VMT fee, or mileage-based user fee (MUBF), is a policy of charging motorists based on how many miles they have traveled. Instead of using a tax on fuel consumption as a way of financing transportation infrastructure, motorists are charged based on their road usage measured in mileage. These charges can be a flat fee (e.g., a fixed number of cents per mile, regardless of where or when the travel occurs), a variable fee based on considerations such as time of travel, congestion levels on a facility, type of road, type, and weight of the vehicle, vehicle emission levels, and the owner's ability to pay, or a combination of flat and variable fees.

In the US, 24 states are actively monitoring road user charge policies and programs, eight have either completed or are in the process of planning an RUC pilot program, and two states have active road user charge programs [237].

F.5.1.1 Advantages Vehicle miles traveled, especially once adjusted for the weight class, is a fiscally-efficient proxy for the costs incurred by NCDOT. Therefore, if structured appropriately, the amount that each vehicle operator pays under an RUC system could closely approximate the share of NCDOT's costs attributable to that vehicle.

For CAVs that are part of corporately owned managed fleets, the necessary data to implement such a charge will likely already be collected by the vehicle owner.

F.5.1.2 Challenges The implementation of such a system would be difficult, especially if imposed on non-CAVs or any CAVs owned by individuals. For these users, location-based systems of administration may raise privacy concerns, while odometer-based systems may be subject to fraud or receive objections from those vehicle owners with significant travel out-of-state or on other non-NCDOT roads (such as city streets or roads on private property). Rural vehicle owners may be especially likely to object, even though most analyses show they would benefit relative to other road users, as rural drivers tend to make fewer, but longer, trips in less efficient vehicles. Unlike most other options, there is currently no infrastructure in place for the collection of an RUC.

In polling asking North Carolinians about their preferred mechanism for funding the state's transportation infrastructure, an RUC was not among the most preferred option; it was, however, most popular among focus group participants [201]. This gap between the views of poll respondents and focus group participants suggests that an RUC's unpopularity in polling may be due to a lack of familiarity among the public.

F.5.2 Motor Fuels Tax reform Under current state law, the Motor Fuels Tax is adjusted annually based on changes in population and in the Consumer Price Index for energy [55]. However, changes in the price of energy are not particularly reflective of changes in NCDOT's costs.

The Motor Fuels Tax could be reformed in a variety of ways, including:

- Annual adjustment to more closely match NCDOT expenditures
- Annual adjustment based on an index of construction costs

⁵The fuel economy of the state's vehicle fleet as a whole, of course, lags that of its newest vehicles.

F.5.2.1 Advantages The Motor Fuels Tax has significant advantages. The administration is exceedingly simple and efficient, with the collection infrastructure already in place, and evasion is difficult. The Motor Fuels Tax also furthers the state’s environmental goals, as fuel consumption is a reasonable proxy for pollution externalities. The state currently has a policy of reducing carbon emissions to 40% below 2005 levels and increasing the number of zero-emission vehicles to 80,000 by 2025 [234].

F.5.2.2 Challenges Over time, as the vehicle fleet moves to CAVs and other vehicles powered by alternative sources of energy, more and more of the burden for building and maintaining North Carolina’s road network will fall upon fewer and fewer motorists—i.e., those who still own conventional gasoline- or diesel-powered vehicles. North Carolina’s motor fuel tax (\$0.405 per gallon including \$0.0025 inspection tax) is only marginally higher than the national average of \$0.3869, this average is brought up by much higher taxes in states like California, Illinois, and Pennsylvania; the median state, Utah, charges \$0.3191 per gallon [131]. More pertinently, North Carolina’s fuel tax is higher than that of its neighboring states—and, in the cases of Tennessee and South Carolina, much higher [116]. Avoidance of the Motor Fuels Tax is possible and is especially easy for those who live close to North Carolina’s borders with its adjacent states, including many residents of the state’s largest metro area, the Charlotte-Concord-Gastonia MSA. Though the current extent of such leakage is not known, the incentive to cross the state border to avoid North Carolina’s Motor Fuels Tax increases as the difference between North Carolina’s rate and that in neighboring states grows.

Fuel consumption is an inferior proxy for a vehicle’s share of capital and maintenance expenditures compared to miles traveled, though it is a superior proxy to the Highway Use Tax and flat fee sources of revenue.

F.5.3 Hypothecated sales tax Retail sales taxes apply to the final sale or lease of most goods and some services. 45 states and the District of Columbia collect a general statewide sales tax. States may also levy selective sales taxes that are used to finance their transportation systems. This may include granting local governments the authority to impose additional tax increments for transportation purposes. From 2013 to 2020, a total of 26 bills related to the use of sales taxes for transportation system funding have been enacted across the United States [225]. All states using the state sales tax method also employ other methods to fund transportation. North Carolina has a state-levied sales tax of 4.75 percent, effective July 1, 2011, with most counties adding a two percent tax, for a total tax of 6.75 percent in 72 of the 100 counties. Among other allowed purposes, the state does allow counties to impose a 0.5 percent sales tax to support public transit, subject to voter approval by popular vote [358]. Durham, Mecklenburg, and Wake counties levy an additional 0.5 percent tax, which is directed toward funding their respective transit systems. The maximum combined state and county sales tax allowed in North Carolina is 7.5 percent. Two counties (Durham and Orange) have met this cap, while the state’s two most populous counties (Wake and Mecklenburg) are 0.25 percentage points below this cap (i.e., the combined rate in these counties is 7.25 percent). In 2022, North Carolina’s general assembly transferred an additional \$193 million in sales-tax revenues to the state highway fund [164]. By 2025, it is anticipated that revenue transfers will triple to \$600 million a year and continue at about six percent of annual sales tax in future years [164].

F.5.3.1 Advantages A small nominal change in the sales tax rate can create large revenues relative to NCDOT’s budget, and the additional costs of implementation and administration are negligible.

Raising the state sales tax was generally the most popular option among poll respondents in North Carolina who asked about their preferences for funding North Carolina’s roads, though no option was ever the first preference of an outright majority [201].

F.5.3.2 Disadvantages One potential pitfall of sales tax diversion stems from the violation of the “user pays” principle. As highway users pay less in motor fuel taxes at the pump and more through general sales taxes, the link between the use of the state’s highway network and funding for the state’s highway network weakens. They may lose the ability to account for how their income is being allocated to transportation. This could lead to motorists perceiving that they are paying less to use the road network. As a result, drivers may drive more and increase roadway congestion. Additionally, North Carolina’s sales tax is regressive by nature, which means those who earn less are required to pay a larger share of their income to support transportation. Some of these unintended consequences can be remediated through policy measures. With North Carolina’s greater focus and awareness of equity issues, measures to alleviate regressive tax impacts should be evaluated.

F.5.4 Highway Use Tax reform North Carolina does not charge sales tax on purchases of motor vehicles. Rather, it charges a Highway Use Tax (HUT) of 3 percent of the purchase price, net of any trade-in value. This level is significantly lower than the base 4.75 state sales tax on most purchases—and much lower than the top rate in some

counties of 7.5 percent. The rate charged in North Carolina is also significantly lower than those charged in most of its neighbors, which can be twice as high or more [55].

The Highway Use Tax currently makes up 17 percent of NCDOT revenues [55].

F.5.4.1 Advantages Administration of the Highway Use Tax is relatively simple, with the necessary mechanisms already in place.

The current lower rate of HUT assessed on vehicle purchases relative to the sales tax charged on other forms of goods consumption acts as a de facto subsidy on automobile purchases. Raising the rate to more closely match those charged on most other purchases would help to eliminate this implicit subsidy.

F.5.4.2 Challenges This would face organized opposition from, among others, motor vehicle dealers. The price of a vehicle is not closely related to NCDOT's costs associated with that vehicle, and, as HUT does not disincentivize marginal driving, it results in the least frequent drivers subsidizing those who drive the most. If CAVs lead to a decrease in vehicle ownership as users instead request "on-demand" rides, the relative number of vehicles on the road would decrease as well, shrinking the HUT base, though this could be offset by the likely higher value of CAVs relative to contemporary vehicles.

F.5.5 Increased fee revenue The Division of Motor Vehicles collects a variety of fees, most notably for title, registration, and licensure. There is also a supplemental registration fee of \$140.25 for electric vehicles, intended to offset lost Motor Fuels Tax receipts. DMV fees currently make up 18 percent of NCDOT revenues. In 2015, these fees were adjusted upwards by 30 percent, and, starting July 1, 2020, are subject to an inflation-based adjustment every four years [55].

NCDOT could shift towards a greater share of the revenue from all drivers and vehicles being fee-derived, or it could continue to increase the amount charged to electric vehicles in particular.

F.5.5.1 Advantages The administration is very efficient, and evasion of these fees is difficult.

F.5.5.2 Challenges Presumably, CAVs would obviate their users' need for a driving license, and the number of licensed drivers would decrease over time, reducing licensure fees as a source of revenue. Similarly, if CAVs result in their users foregoing car ownership, the relative size of the vehicle fleet may decrease as well, reducing fee revenue from titling and registration. Moreover, as these fees are charged per vehicle, this decrease would not be offset by the higher value of CAVs (see Highway Use Tax reform above). These challenges could be offset, however, through increased rates.

A flat-rate fee on a vehicle or driver is a very poor proxy of the capital and maintenance expenditures associated with that vehicle or driver. Those who drive the least would subsidize those who drive the most, and drivers would be incentivized to drive more than they would otherwise were they bearing the actual marginal cost of their driving.

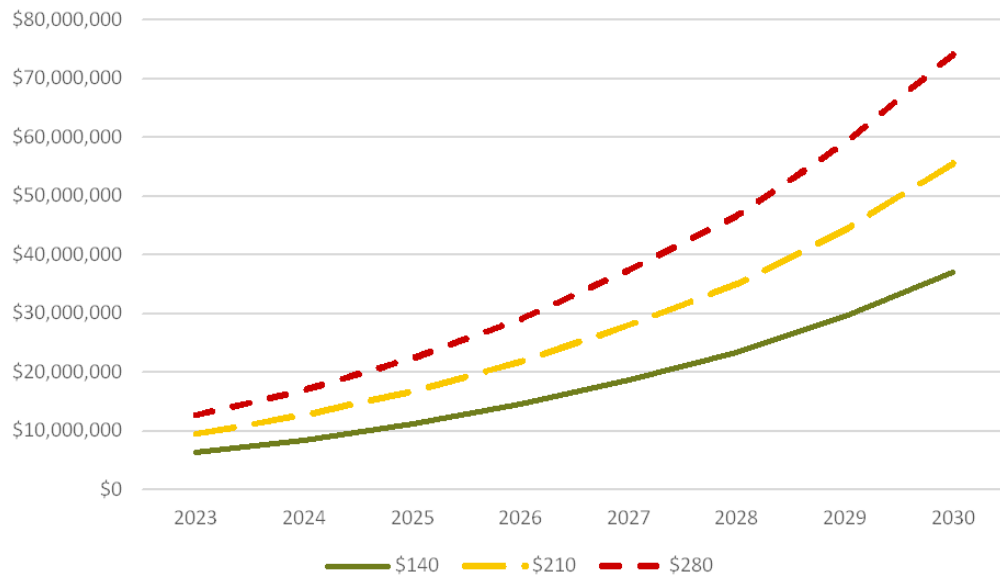
As discussed (see Electrification above), the existing additional fee charged for EVs likely exceeds the Motor Fuels Tax that would be collected on similar conventionally powered vehicles, and an increase may act as a further effective subsidy to gasoline vehicles, which may be contrary to non-revenue policy goals, such as the state's current goal of reducing carbon emissions to 40% below 2005 levels and increasing the number of zero-emission vehicles to 80,000 by 2025 [234].

F.5.5.3 Revenue projection The amount of revenue raised from the EV supplemental registration fee depends on the rate selected. Fig. 117 compares the projected revenue raised from the current fee compared to that from raising the fee by 50% and by 100%, based on NCDOT's current forecast of electric vehicle adoption. As shown in Fig. 118, however, any of these rates are expected to exceed lost MFT in the year 2025.

F.5.6 Taxes on alternative fuels Some states have imposed taxes on non-gasoline/diesel fuels used for vehicle operation, including not only other hydrocarbons like propane or natural gas but even electricity. North Carolina already taxes ethanol propane, compressed natural gas, and liquefied natural gas on a gasoline-gallon or diesel-gallon equivalent basis [44].

F.5.6.1 Advantages Unlike flat rate fees, and like the Motor Fuels Tax or a Mileage-Based User Fee, taxes based on fuel consumption preserve the disincentive on marginal driving and lessen the subsidy from those who drive the least to those who drive the most.

F.5.6.2 Challenges Collection and compliance enforcement for a tax on electricity used specifically by CAVs and electric vehicles may be difficult. No existing method exists for the collection of such a tax, and segregating electricity used for vehicles from that used for other purposes may be challenging to do in a reliable way. For example,



Source: Authors' illustration

Figure 117. Projected EV supplemental registration fee revenue at various rates



Sources: Authors' illustration; (Brutz & Carr, 2019)

Figure 118. EV supplemental fee vs lost MFT, 2025

Pennsylvania requires drivers to record usage and calculate, report, and remit the tax owed [58], while a proposed tax in Iowa would only be charged at locations “other than a residence” [11]. It is possible, though, that corporate fleet owners of CAVs will be more capable and willing to comply with a tax that required reporting consumption of electricity for the purpose of vehicle charging than would be individual vehicle owners.

The correct basis for rate determination may also be difficult. Pennsylvania’s tax is based on the energy content of the alternative fuel and designed to be equivalent to on this basis to the state’s gasoline tax [58]. In 2023, Iowa will begin charging a rate that is 50 percent higher per kilowatt-hour than that charged in Pennsylvania [58]—despite its gasoline tax is roughly half that of Pennsylvania’s [131])—and which will be collected in addition to a supplemental registration fee of \$130 [11].

F.5.7 Increased toll revenue As of 2021, there are three tolled facilities in North Carolina, with four more projects underway [55] [224]. Currently, state law requires that tolls must be used on the same project from which they were collected or on a contiguous facility [9]. Toll revenues could be increased in a variety of ways:

- State law could be changed to allow toll revenues to be used for other NCDOT purposes.
- Additional tolled facilities could be constructed.
- Tolling could be added to existing facilities.

F.5.7.1 Advantages Similar to an RUC, a well-calibrated toll can be an extremely accurate proxy for a vehicle’s capital and maintenance burden on the tolled roadway itself. Tolls, therefore, align with the “user pays” principle on highways on which they are charged.

F.5.7.2 Challenges Using toll revenues for NCDOT purposes other than the facility on which the toll was collected violates the “user pays” principle.

The construction of new tolling facilities and the introduction of tolling to existing facilities are time-consuming and require significant upfront capital investment. It is unlikely that such investments will ever be in North Carolina on roads that are not limited-access highways.

The addition of tolling to existing facilities would likely encounter significant public resistance. Furthermore, section 129 severely curtails the state’s ability to toll existing Interstate and other Federal-aid highways, with only narrow exception [92].

F.5.8 State appropriations Currently, NCDOT relies on hypothecated (or dedicated) revenue streams to fund its operations. This is quite unlike most other state agencies, few of which are almost entirely dependent on dedicated revenue sources and most of which instead rely primarily on appropriations from the North Carolina General Assembly, which appropriates funds by weighing agency needs against available revenues. NCDOT could transition to being funded more like other state government agencies.

F.5.8.1 Advantages In general, expenditures tend to rise to fill the available funds, both for individuals and for organizations. If department funds were appropriated by the General Assembly instead of set by hypothecation, there would be a greater ability to match available funds with NCDOT’s actual expenditure needs. Correspondingly, there would also be greater public oversight and scrutiny of NCDOT spending.

F.5.8.2 Challenges Relying on state appropriations does not solve a potential revenue shortfall at NCDOT. Rather, it simply shifts the problem elsewhere. Funding for North Carolina’s transportation network will still need to be found, just from other potential revenue sources, such as income, sales, corporate income, and franchise taxes, or from reduced expenditures elsewhere. Furthermore, the “user pays” principle would be significantly weakened. Finally, relying on appropriations may reduce the stability of NCDOT funding, hampering future planning.

F.5.9 Introduce a tax or fee on for-hire vehicle trips A tax or fee could be charged on for-hire vehicle (FHV) journeys, either only those taken in CAVs, only those in EVs, or those in all FHVs. Currently, in North Carolina, trips in “ridesharing” vehicles are entirely untaxed—including being free of sales tax—and local taxes and fees on such trips are also prohibited. Only 11 other states take North Carolina’s tax-lite approach to such journeys [162].

F.5.9.1 Advantages FHV journeys are expected to be a common application of CAVs. A tax or fee could be administratively simple to operate. A per-trip fee would be transparent and easy to calculate, increasing its salience.

F.5.9.2 Disadvantages A fee charged either per trip or as a percentage of the fare charged would be a poor proxy for the costs that a trip imposes on NCDOT. A fee charged to users per VMT would not be transparent to users

and would be a worse proxy for the costs imposed than an RUC charged on the operator on all vehicle miles traveled (see Implementation of a Road User Charge above). (An RUC charged to operators only on VMTs when a vehicle is occupied would have equal incidence to a per VMT fee charged to a passenger on a private journey, i.e., the economic and tax consequences of these would be equivalent for all parties, despite the tax supposedly being owed by a different entity.)

The General Assembly has been reluctant to impose taxes specifically on “ridesharing” trips.

F.5.10 Transfer of facilities North Carolina has an unusually large state highway system. There are no county roads in North Carolina: a public road is maintained either by the local municipality or by the state itself. Many seemingly local roads in North Carolina are maintained by NCDOT and not by the municipality in which they are located. As a result, North Carolina’s state-maintained highway system comprises nearly 80,000 miles, second only to that of Texas. North Carolina could choose to adopt a system more similar to that of most other states, where municipalities and/or counties take on a greater share of the responsibility for maintaining local roads.

F.5.10.1 Advantages NCDOT would face lower maintenance costs due to the transfer of facilities to other entities.

F.5.10.2 Disadvantages This proposal would almost certainly face unified opposition from North Carolina’s 552 municipalities and 100 counties. Currently, there are no county roads in North Carolina. Counties do not now have the physical or organizational infrastructure to accept this responsibility. Moving responsibility for a greater share of North Carolina’s roadways to lower tiers of government does not solve a potential revenue shortfall. Rather, it simply shifts the problem from NCDOT to local governments. Funding for North Carolina’s transportation network will still need to be found, just from the other potential revenue sources that are available to local governments, such as local property and sales taxes.

F.5.11 Other mechanisms

F.5.11.1 Hypothecated income tax A diversion of a portion of North Carolina’s state personal income tax would, similar to that of sales tax, create large revenues relative to NCDOT’s budget with negligible implementation and administration costs. There would, however, be, significant challenges to taking such a measure. The state constitution caps the personal income tax rate at 7%, but North Carolina’s rate, which as of January 2023 is a flat rate of 4.99 percent, has been successively cut over the last decade and is scheduled to continue to decrease to 3.99 percent by 2027 [193]. A dedication of a portion of income tax for the state’s transportation needs would be competing for increasingly constrained funds with the many other state policy priorities funded by income tax. Moreover, diverting income tax would suffer from the same violation of the “user pays” principle as the dedication of sales tax (see Hypothecated sales tax, above).

F.5.12 New taxes or fees on non-motorists Motorists are not the only users of NCDOT highways. Bicyclists, pedestrians, and transit riders benefit from these facilities, as well. Additional fees, such as an additional sales tax or registration fee for bicycles or a fee for transit trips, have been proposed. However, expenditures imposed by these groups are minimal, implementation and administrative costs would be high, and there are significant environmental and economic equity concerns when increasing costs on these road users. Most pedestrians, cyclists, and transit users are also motorists, and all pay state sales tax on their retail purchases. Moreover, transit vehicles do currently incur at least some of the taxes and fees that owners of other vehicles must pay.

F.5.13 Tire tax Due to the additional infrastructure burden imposed by the heaviest vehicles, purchases of tires with a maximum rated load greater than 3,500 lbs. are subject to an additional tax at the Federal level of \$0.0945 for every 10 lbs. of rated load above 3,500 lbs.

North Carolina could consider paralleling this measure with a state tax. This would not raise a great deal of revenue on its own nor would it be effective in capturing costs from out-of-state vehicles traveling on North Carolina roads. Furthermore, unlike its Federal counterpart, a state tire tax would be more prone to avoidance from the shifting of registrations of commercial vehicles outside the state and/or to evasion from out-of-state tire sales for North Carolina-registered vehicles.

A tire tax could also be implemented for all tires sold in the state. Such a tax would face similar challenges, though at a greater scale: a tax low enough to minimize avoidance would raise little revenue, while a high tax rate would result in widespread avoidance.

E.6 Conclusion

As North Carolina's vehicle fleet, demographics, and consumer preferences change, NCDOT will struggle to meet its expenditure needs from its existing sources of revenue, and new funding will need to be identified and implemented. Multiple options for this exist, including reforms to existing sources as well as the creation of new revenue streams. Ultimately, the state will likely need to adopt a blend of multiple approaches.

APPENDIX: G.4

Develop Guideline on the Intersection Capacity Adjustments Considering Different Level of CAV Market Penetration

Appendix G : Develop Guideline on the Intersection Capacity Adjustments Considering Different Levels of CAV Market Penetration

G.1 Introduction

Based on the results in Task 4 and Appendix B.5, a comprehensive set of guidelines is developed for calculating the intersection capacity considering different CAV MPRs. The lane-level and intersection-level capacity analysis methodologies are developed to accurately capture the impacts of CAV technologies on the intersection system. Detailed adjustment lookup tables and fitting equations are comprehensively documented during the course of this research. Best practices are also recommended for improving the intersection system by incorporating the use of CAVs in the future.

The following sections are organized as follows. Section G.2 presents the lane-level and intersection-level methods for the intersection capacity analysis considering mixed traffic environments. Section G.3 summarizes lane-level and intersection-level capacity adjustment factors under different MPRs of CAVs. The lane-level adjustment factors for saturation headways and saturation flow rates are comprehensively documented. Meanwhile, intersection-level adjustment factors for the maximum throughput of the intersection and fitting equations for traffic performance indicators are presented. Finally, This chapter concludes with a summary.

G.2 Methods for Intersection Capacity Analysis

The microscopic simulation method is implemented in this research to investigate the impacts of CAVs on the intersection capacity. The main difference between the HDVs and CAVs in the microscopic simulation model is the control mode of longitudinal movement, which mainly controls the acceleration/deceleration, speed, car following gaps, etc. In this research, The IDM is implemented for modeling HDVs. The ACC system is utilized to model CAVs when the CAV is following a HDV. The CACC system is implemented to model CAVs when the CAV is following a CAV. The longitudinal movement controls of the CAVs are expected to significantly improve the efficiency of the roadway/intersection systems.

All simulation scenarios are processed in the SUMO by the TraCI-Python interface. The default lane change model “LC2013” in SUMO is employed for all vehicles. The desired headways for HDVs and CAVs are 1.9 s and 0.6/1.1 s, respectively. Also, other parameters for CACC-controlled CAVs are set according to previous research and projects [187,208,255].

The intersection capacity is first analyzed by calculating adjustment factors for saturation headway and saturation traffic flow rate for each lane under different MPRs of CAVs. Then, the maximum throughput and other traffic performance indicators of the whole intersection under different MPRs of CAVs are calibrated and investigated. The details of the lane-group-level and intersection-level capacity analysis methods are summarized as follows:

G.2.1 Lane-level Capacity Analysis Method To determine the capacity of the intersection, the saturation flow of each lane is calculated. The saturation flow s_0 is the maximum traffic that a lane could accommodate per hour. In this research, the simulation method is used to calculate the saturation headway and the adjustment factors with regard to CAV penetration rates. As shown in equation (G.1), the basic saturation headway rate s_0 is obtained by dividing 3600 s with the saturation headway of human driving vehicles h_{HDV} .

$$S_0 = \frac{3600}{h_{HDV}} \quad (G.1)$$

As defined in HCM2016 [117], saturation headway is calculated by the average headway between the fifth and fifteenth passenger cars in a standing queue when the intersection signal changes from red to green. The first four headways are not included due to the start-up loss time. In the simulation, the headway is calculated by the time gap when two successive vehicles (front bumper) are passing over the stop line. Considering the impacts of CAV penetration rates, the h_{HDV} and headways with the mixed traffic (h_{CAV}) could be obtained from the simulations. Then, the headway adjustment factor f_h could be obtained by the equation (G.2). The adjusted saturation flow rate s^* could be adjusted by the headway adjustment factor f_h according to equation (G.3) or the saturation flow rate (SFR) adjustment factor f_s according to equation (G.4).

$$f_h = \frac{h_{CAV}}{h_{HDV}} \quad (G.2)$$

$$S^* = \frac{3600}{f_h \times h_{HDV}} \quad (G.3)$$

$$S^* = f_s \times s_0 = f_s \frac{3600}{h_{HDV}} \quad (G.4)$$

With the headway adjustment factor f_h or the saturation flow rate adjustment factor f_s , the adjusted saturation flow rate for each lane group under different MPRs of CAVs could be calculated. The total capacity of the intersection is computed by the product of the adjusted saturation flow rate and effective green time per cycle ratio. Then the signal intersection capacity is expressed as an hourly rate (or 15 minutes of the peak hour), with the unit of vehicles per hour. The capacity of the signal intersection is the sum of the lane group capacity,

$$\text{Capacity} = \sum_i s_i^* \frac{g_i}{C} \quad (G.5)$$

where s_i^* indicates the saturation flow rate of the critical lane group i . g_i/c is the effective green time per cycle ratio for lane group i .

With the estimated adjustment factors for the saturation headway f_h or the saturation flow rate f_s , the Quick-Estimation Method (QEM), which is introduced in the Highway Capacity Manual [117], is used to calculate the whole intersection capacity. The QEM determines the critical movements based on the signal phases and calculates the critical phase volumes. Then the intersection capacity is calculated based on the maximum traffic volume that the intersection could accommodate in an hour. The main steps of QEM are listed as follows:

Step 1: Identify intersection traffic movements, the number of lanes, and calculate hourly traffic volumes per lane. Usually, the hourly traffic volumes are modified to represent the peak 15-minute period.

Step 2: Design a signal phasing plan and determine the traffic movements in each phase. Each phase usually accommodates two nonconflicting movements. The treatment (protected, permitted, etc.) of each left-turn movement is determined mainly based on the left-turn volume and the opposing through-traffic volume.

Step 3: Determine the critical volume per lane group that must be accommodated for each phase. The lane group is divided by the traffic movements in each phase. For example, the exclusive left-turn lane with a protected left-turn phase is usually designated as a specific lane group. The critical movement volume determines the amount of green time that should be assigned to the phase on one signal cycle.

Step 4: Sum the critical phase volumes per phase to determine the overall critical volume that the intersection needs to accommodate.

Step 5: Calculate the overall intersection capacity by determining the maximum critical volume that the intersection can accommodate per cycle. The maximum critical volume is determined by the adjusted saturated traffic flow. For signal-controlled intersections, the HCM QEM recommended 1,710 vph. as a base value for the saturation flow rate with only human-driving vehicles for most purposes. For scenarios with different MPRs of CAVs, the basic s_0 is modified by the adjustment factors of the saturation flow rate.

G.2.2 Intersection-level Capacity Analysis Method

In microscopic simulation scenarios, saturation traffic throughput (or maximum throughput) is utilized to estimate the capacity of the intersection. The HCM defines capacity as the maximum number of vehicles that can pass through the intersection under certain traffic, roadway, and signalization conditions. The traffic generation in the simulation obeys the uniform distribution to maintain the peak-hour traffic demands all the time. Each simulation maintains 3600 s with a 0.1 s time step. Meanwhile, a ten-minutes (600 s) warm-up period is added at the beginning of each simulation. This warm-up period aims to eliminate the impacts of insufficiency of traffic generation at the first ten minutes of the simulation.

For simulation scenarios with different MPRs of CAVs (increase from 0% to 100% by 10% per step), the maximum throughput is obtained by increasing the traffic demands of the intersection. The maximum throughput value is determined if the throughput reaches a stable value with the increase of traffic demand in the following five simulations. Then, the traffic performances (including maximum throughput, total waiting time, total CO2 emission, and total fuel consumption) for the simulation with the maximum throughput are also documented to investigate the impacts of CAV penetration rates on the intersection.

G.3 Adjustment Lookup Tables

In this section, the adjustment factors for the lane-level and intersection-level capacity are all summarized and documented. In the lane-level capacity investigation, adjustment factors for saturation headway and saturation

Table 49. Adjustment factors for saturation headway and saturation flow rate for each lane group under different MPRs of CAVs

	Saturation headway adjustment factors			Saturation flow rate adjustment factors		
CAV rate	Exclusive through	Exclusive left	Shared right	Exclusive through	Exclusive left	Shared right
0.1	0.984	0.98	0.967	1.016	1.02	1.034
0.2	0.958	0.959	0.977	1.044	1.043	1.024
0.3	0.884	0.869	0.938	1.131	1.151	1.066
0.4	0.823	0.852	0.883	1.215	1.174	1.133
0.5	0.821	0.847	0.835	1.218	1.181	1.198
0.6	0.74	0.748	0.815	1.351	1.337	1.227
0.7	0.645	0.698	0.743	1.55	1.433	1.346
0.8	0.632	0.638	0.716	1.582	1.567	1.397
0.9	0.505	0.548	0.655	1.98	1.825	1.527
1	0.441	0.511	0.576	2.268	1.957	1.736

Table 50. Traffic performance under saturated traffic flow with different MPRs of CAVs

MPR	Traffic demand	Total waiting time (s)	Average waiting time (s)	Total CO2 (kg)	Avg. CO2 (kg)	Total Fuel (L)	Avg. Fuel (L)	Maximum Throughput	Adj. Factor
0	5400	658796.4	122	2180.461	0.404	937.329	0.174	4938	
0.1	5600	697819	124.61	2385.617	0.426	1025.52	0.183	5047	1.022
0.2	5600	695985.4	124.28	2282.991	0.408	981.403	0.175	5155	1.044
0.3	6100	860257.7	141.03	2922.059	0.479	1256.132	0.206	5339	1.081
0.4	6200	848790.4	136.9	2854.666	0.46	1227.158	0.198	5565	1.127
0.5	6500	906076.3	139.4	3001.592	0.462	1290.318	0.199	5844	1.183
0.6	6500	787004.7	121.08	2662.238	0.41	1144.432	0.176	6085	1.232
0.7	6800	734282.3	107.98	2636.286	0.388	1133.273	0.167	6494	1.315
0.8	7400	955250	129.09	3204.906	0.433	1377.712	0.186	6973	1.412
0.9	8000	1008473.3	126.06	3539.99	0.442	1521.757	0.19	7568	1.533
1	8900	1157348.1	130.04	4323.411	0.486	1858.534	0.209	8413	1.704

traffic flow rate for each lane group under different MPRs of CAVs are summarized. In the intersection-level capacity investigation, the maximum throughputs of the intersection under different MPRs of CAVs are all documented. Also, the fitting functions for the maximum throughput, total waiting time, total CO2 emission, and total fuel consumption under different MPRs of CAVs are calibrated.

G.3.1 Lane-level Adjustment Factors

With the increase of the traffic demands for each lane group, the intersection throughput reaches a maximum value which represents the saturated traffic demands. In this study, each approach of the intersection includes one exclusive through traffic lane, one exclusive left-turn traffic lane, and one shared right and through traffic lane. Table 49 summarizes the adjustment factors for saturation headway and saturation flow rate for each lane under different MPRs of CAVs. The change rates are compared to the base scenario with only human-driven vehicles. Under 100% MPR of CAVs, the saturation headway of through-only, left-only, and shared right and through traffic lanes are about 0.441, 0.511, and 0.576 with respect to the basic headway with only human-driven vehicles. Meanwhile, with 100% MPRs of CAVs, the maximum saturation flow rates for the through, left-only, and shared-right lanes could increase by about 126.8%, 95.7%, and 73.6%, respectively.

G.3.2 Intersection-level adjustment factors

For the intersection-level simulation, the maximum throughput of the isolated intersection is obtained with the increase in traffic demands. The capacity (i.e., maximum throughput) of the isolated intersection is obtained in the simulation under different MPRs of CAVs conditions. The traffic performances are also investigated under maximum throughput scenarios. Table 50 summarizes the maximum throughput and other traffic performance indicators of the intersection under different MPRs of CAVs. The change rates of the maximum throughput (i.e., adjustment factors of the maximum throughput) compared to the 100% HDV scenario are listed in the last column. The maximum throughput increases steadily under 60% MPRs of CAVs and increases rapidly after 70% MPRs of CAVs. With the increase in traffic throughput, the total CO2 emission, total fuel consumption, and total waiting time also increase significantly after 70% MPRs of CAVs.

With the results in Table 50, the fitting functions of the maximum throughput (veh/hour), total CO2 emission (kg), total fuel consumption (L), and total waiting time (10^6 s) of the saturated traffic flow with regard to different

MPRs of CAVs are also summarized as follows:

$$\text{MaximumThroughput} = 2969\text{MPR}^3 - 1010\text{MPR}^2 + 1505\text{MPR} + 4914 \quad (\text{G.6})$$

$$\text{CO}_2 = 9003\text{MPR}^3 - 11800\text{MPR}^2 + 5023\text{MPR} + 2052 \quad (\text{G.7})$$

$$\text{Fuel} = 3870\text{MPR}^3 - 5074\text{MPR}^2 + 2159\text{MPR} + 882.1 \quad (\text{G.8})$$

$$\text{WaitingTime} = 2.166\text{MPR}^3 - 2.96\text{MPR}^2 + 1.332\text{MPR} + 0.6208 \quad (\text{G.9})$$

G.4 Summary

This Section summarizes the methods for lane-level and intersection-level intersection capacity analysis. In the lane level capacity investigation, adjustment factors for saturation headway and saturation traffic flow rate for each lane under different MPRs of CAVs are calculated. In the intersection level capacity investigation, the maximum throughputs of the intersection under different MPRs of CAVs are calculated. The traffic performances of the total waiting time, CO2 emission, and fuel consumption under maximum throughputs are also documented. The detailed adjustment lookup tables and fitting equations are comprehensively documented. Traffic engineers and planners are expected to be able to directly use the proposed simulation methods or the adjustment factors to calculate the intersection capacity under different MPRs of CAVs.

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