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

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16. Abstract

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

.... conducting multidisciplinary research under the 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 project leverages the results that were achieved in the first phase of the center in order to conduct three new projects, including:

- *Project #4: Assessing the Impact of Connected and Automated Vehicles on Work Zones*
- *Project #5: Evaluating Connected and Secure Edge Infrastructure for Scalable Hardware-in-the-Loop North CAV*
- *Testbeds*
- *Project #6: Define and implement potential use cases for deployment of CAVs.*

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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. Building upon the foundational accomplishments of Phase 1, Phase 2 of the NC Transportation Center of Excellence on Connected and Autonomous Vehicle Technology (NC-CAV) leveraged prior results to conduct three major projects:

1. **Project #4:** Assessing the Impact of Connected and Automated Vehicles on Work Zones,
2. **Project #5:** Evaluating Connected and Secure Edge Infrastructure for Scalable Hardware-in-the-Loop North CAV Testbeds,
3. **Project #6:** Define and implement potential use cases for deployment of CAVs.

The Center researchers investigated how increasing CAV adoption will influence safety and operational performance in complex roadway environments, particularly work zones. Work zones represent some of the most challenging and high-risk segments of the transportation system, characterized by changing geometries, reduced lanes, dynamic traffic control, and heightened crash exposure. The research team developed calibrated microscopic traffic simulation models capable of analyzing mixed traffic fleets that include both human-driven vehicles and varying levels of CAV market penetration. Through structured simulation experiments under low, medium, and high demand conditions, the study quantified impacts on throughput, delay, time-to-collision safety surrogate metrics, and emissions. Results demonstrated that coordinated CAV behavior can reduce traffic instability, improve throughput, and lower potential crash risk, particularly as penetration rates increase. At the same time, the analysis identified transitional effects during partial adoption phases, providing NCDOT with realistic expectations and implementation considerations. These findings equip NCDOT with evidence-based guidance for work zone design, temporary traffic control planning, and long-term infrastructure adaptation strategies in a progressively automated vehicle environment.

In parallel with operational impact assessment, the Center researchers advanced North Carolina's readiness for next-generation digital transportation infrastructure. The project developed and validated a Software-Defined Vehicular Edge Computing (SDVEC) architecture that enables secure, real-time communication and computation between connected vehicles and infrastructure. Hardware-in-the-Loop (HIL) testbeds were implemented to integrate physical autonomous vehicle platforms with simulated transportation environments, allowing algorithms, networking protocols, and system architectures to be evaluated under realistic operating conditions prior to field deployment. This capability significantly reduces implementation risk, accelerates technology validation, and provides NCDOT with a scalable platform for evaluating future mobility solutions. In addition, the project established digital twin frameworks using C-V2X communication models to synchronize physical systems with virtual simulations in real time. These digital twins enable performance testing, infrastructure planning, and system optimization without requiring full physical deployment, thereby offering NCDOT a strategic tool for cost-effective modernization. Recognizing that connected and automated systems introduce new cybersecurity challenges, the Center researchers incorporated robust security evaluation and mitigation strategies. The research team developed real-time intrusion detection systems tailored for autonomous vehicle ecosystems and evaluated federated learning approaches to strengthen adversarial resilience. Performance assessments examined detection accuracy, resource efficiency, and robustness under simulated attack scenarios. The resulting recommendations provide NCDOT with a forward-looking cybersecurity roadmap to support safe scaling of connected infrastructure while protecting against emerging digital threats. Integrating cybersecurity considerations at the infrastructure design stage strengthens system reliability, safeguards public trust, and ensures long-term operational resilience.

Beyond modeling and infrastructure development, in this phase, the Center emphasized practical deployment use cases to demonstrate how CAV technologies can improve real-world transportation performance. A distributed, cloud-based on-demand ridesharing framework was developed, incorporating advanced demand prediction, routing optimization, and pricing strategies. Simulation and prototype evaluations demonstrated improved fleet utilization and service efficiency. Additionally, the project quantified the operational effects of CAV penetration at roundabouts and implemented coordinated vehicle trajectory control strategies to enhance capacity and reduce congestion. Real-world demonstrations using connected autonomous vehicles validated these improvements and illustrated the feasibility of coordinated control supported by cloud and edge communication systems. The development of a cloud-based ride-sharing application compatible with CAV testbeds further demonstrated scalable deployment potential, integrating ROS2 communication, WebSocket interfaces, and 5G connectivity for real-time coordination. These applied implementations move the Center's work beyond theory and provide NCDOT with concrete examples of deployable innovation.

The accomplishments of Phase 2 of NC-CAV Center extend beyond technical outputs to include workforce development, research dissemination, and strategic partnership building. The Center trained graduate and undergraduate students in advanced transportation technologies, strengthening North Carolina's future transportation workforce. Through seminars, publications, and collaboration with federal agencies and industry partners, the Center enhanced the state's visibility and competitiveness in national CAV research initiatives. These activities position North Carolina as a leader in advanced transportation systems innovation and create pathways for continued federal and private investment.

The benefits of this work to NCDOT and the transportation systems of North Carolina are substantial. From a safety perspective, the research provides quantifiable evidence supporting reduced collision risk and improved traffic stability in work zones and other high-conflict environments. From an operational standpoint, the modeling and deployment efforts demonstrate opportunities to improve throughput, reduce congestion, and optimize system performance under mixed fleet conditions. From an infrastructure perspective, the validated edge computing and digital twin architectures provide a clear roadmap for modernization of communication and computational capabilities necessary for future mobility systems. From a cybersecurity standpoint, the developed detection and mitigation strategies strengthen resilience against emerging threats. Environmentally, coordinated CAV operations show potential to reduce emissions and support sustainability goals. Strategically, the project enables NCDOT to plan proactively for technology adoption rather than reactively responding to industry disruption.

In summary, Phase 2 of the NC-CAV Center successfully transformed foundational research into scalable, secure, and deployment-ready transportation innovations. By integrating safety analysis, infrastructure modernization, cybersecurity resilience, operational modeling, and workforce development, the Center provides NCDOT with the tools and knowledge required to lead the responsible integration of connected and autonomous vehicle technologies. This work ensures that North Carolina is positioned not only to accommodate technological transformation but to shape and guide it in a manner that enhances safety, efficiency, sustainability, and economic competitiveness across the state's transportation network.

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1.1 Background

Work zones have a negative impact on traffic efficiency and safety due to the introduction of variance in traffic speed and driving behavior. According to the estimation from the US Federal Highway Administration (FHWA), work zones account for roughly 10% of the total road delay in the US. This delay percentage ranks behind recurring bottlenecks (40%), traffic crashes (25%), and inclement weather (15%) [45]. In addition to the adverse impact on mobility, work zones also result in severe traffic crashes, as evidenced by statistics from the North Carolina Department of Transportation (NCDOT), which recorded 29 fatalities and 2500 injuries among 6200 crashes in work zones in 2021 [113]. These statistics underscore the importance of investigating advanced technologies that have the ability to alleviate the adverse impacts of work zones on mobility and safety.

It is widely accepted that CAV technologies will have the potential to significantly improve the mobility and safety of transportation systems. By enabling vehicles to communicate with other vehicles and infrastructure in real-time and to maneuver without human intervention, CAVs can enhance mobility through shorter headways, faster reactions, and more accurate controls. Additionally, CAVs can eliminate up to 94% of crashes attributed to human errors [72, 199], which is a dramatic improvement in terms of safety. The availability of connection and automation also provides the potential to significantly enhance the management of work zones. Therefore, the impact of the development of CAV technology on work zones is an imperative research thrust.

The product of this research will be a comprehensive analysis of the impact of CAV technology on work zones at various CAV market penetration rates and under different traffic situations, with a focus on the domain of mobility and safety. While the study acknowledges the potential environmental impact of CAVs in work zones, this aspect will not be the primary focus of the research. By investigating the potential benefits of CAV technology in work zones, this research will inform the development of strategies to enhance mobility and safety in work zones and contribute to the overall improvement of transportation systems.

The main goal of this research project is to investigate the impacts of CAVs on work zones and to identify strategies for integrating CAVs into work zones to enhance safety and efficiency. The objectives of this project are to:

- **Objective 1:** Conduct a comprehensive review of existing literature related to CAVs and work zones in order to identify gaps in knowledge and inform the research design.
- **Objective 2:** Identify and design work zones from real-world highways as potential scenarios.
- **Objective 3:** Create a simulation model to analyze the impacts of CAVs on work zones under different scenarios. The simulation model will consider variables such as work zone configurations, traffic volume, and CAV penetration rates.
- **Objective 4:** Develop a case study of the successful implementation of CAVs in a work zone to identify best practices and strategies for integrating CAVs into work zones.
- **Objective 5:** Conduct in-depth analysis and integrate results from this project, including refining insightful findings and providing recommendations for future research directions.

1.2 Task 1: Literature Review

1.2.1 Introduction Connected and Autonomous Vehicles are expected to significantly transform roadway safety, mobility, and traffic operations. Work zones represent one of the most complex and safety-critical roadway environments due to temporary geometry, lane closures, speed variability, and elevated crash risk. Understanding how CAV technologies interact with work zones is therefore essential for developing future traffic control strategies and simulation frameworks.

This summary synthesizes existing research on Connected Vehicles (CVs), Autonomous Vehicles (AVs), and integrated CAV systems, with emphasis on their safety, mobility, and operational impacts in work zone environments.

1.2.2 Connected Vehicles Connected Vehicles use wireless communication technologies to exchange real-time information with other vehicles, infrastructure, and cloud systems through V2V and V2I communication [163]. Technologies such as Dedicated Short-Range Communication (DSRC) and cellular networks enable vehicles to share speed, position, and traffic conditions, supporting hazard warnings and traffic management [117].

CVs improve situational awareness and allow drivers to respond to hazards more quickly. These technologies aim to reduce crashes, enhance traffic flow, and support proactive traffic management strategies.

1.2.3 Autonomous Vehicles Autonomous Vehicles are capable of performing driving tasks without direct human control. The SAE six-level automation taxonomy ranges from Level 0 (no automation) to Level 5 (full automation) [115]. AVs rely on sensors such as LiDAR, radar, and cameras to perceive their environment and employ advanced safety systems and redundant hardware to ensure safe operation .

1.2.4 Connected and Autonomous Vehicles CAVs combine connectivity and automation, enabling vehicles to make decisions using both onboard sensors and shared external data. This integration reduces reaction variability and enables coordinated driving behavior, supporting improved safety and traffic efficiency.

1.2.5 Potential Benefits of CAV technology

- **Safety:** Human error contributes to over 90% of crashes [114]. CAVs can reduce these errors through consistent rule compliance, rapid hazard detection, and predictive safety systems . Sensors allow detection of vulnerable road users, improving pedestrian and cyclist safety [65].
- **Mobility and Capacity:** Coordinated driving enabled by V2V communication can reduce stop-and-go traffic and improve traffic flow. Shorter headways and optimized routing increase roadway capacity and reduce congestion .
- **Environmental Impacts:** CAVs can improve fuel efficiency through smoother driving and optimized routing . Integration with electric vehicle fleets could reduce emissions substantially . However, increased travel demand and empty vehicle trips may offset environmental gains .

1.2.6 Work Zone Characteristics and Safety Challenges Work zones are temporary roadway segments where construction or maintenance alters normal traffic flow . These environments introduce lane closures, merging behavior, speed variability, and driver uncertainty.

Work zones are associated with increased crash rates. Rear-end collisions are the most common crash type . Nighttime work zones show elevated fatal crash risk due to reduced visibility, while daytime crashes are often linked to higher traffic volumes . Work zones also increase congestion and emissions due to traffic delays.

1.2.7 CV and (or) AV Technology in Work Zone Environment This section of the report provides a comprehensive review of pertinent literature concerning work zones and Connected and Autonomous Vehicles (CAVs). Existing studies are summarized in Table 1

Table 1. Summary of Literature on CAVs in Work Zones

Study	**Objective**	**Methodology**	**Data Source**	**Key Findings**
Olia et al. (2012) [122]	Address congestion from infrastructure projects using CV systems	Microscopic simulation modeling traffic dynamics and CV system impacts	Modeled O-D matrix using gravity model (based on free-flow travel time)	CV systems reduce congestion and improve mobility and safety
Qiao et al. (2014) [131]	Explore RFID-based Driver Smart Assistance System for work zone safety	Field tests with 20 drivers using RFID communication	Human subject experiment	System improves driver compliance and reduces emissions, enhancing safety
Genders and Razavi Saiedeh (2016) [47]	Assess impact of CAVs on work zones with a dynamic route guidance system	Simulation using Paramics with V2V communication; Conservative, Moderate, Liberal driver models	Simulation traffic data	Higher Market Penetration Rate (40%) may reduce safety due to prioritizing time savings over distance
Ramadan (2016) [134]	Evaluate merge control strategies for long-duration work zones	Microsimulation for peak and off-peak traffic conditions	Empirical traffic data (GPS speeds, manual volume counts)	Merge strategies improve mobility and safety, challenging preference for off-peak scheduling
Zou and Qu (2018 [215]	Assess impact of CAVs on freeway work zone traffic operations	Cellular automata model simulating collaborative CAV behavior	Simulation traffic data	CAVs improve travel time, safety, and emissions, reducing operational variability
Abdulsattar et al. (2018) [3]	Assess safety impacts of CV technologies with different penetration rates and traffic conditions	Agent-Based Modeling and Simulation (ABMS) framework	Simulation traffic data	Higher CV penetration needed to achieve safety benefits, especially under high traffic
Abdulsattar et al. (2020) [2]	Evaluate mobility benefits of CVs in work zones on a two-lane highway	Agent-based modeling for V2V and V2I communication, varying traffic flow scenarios	Simulation traffic data	Mobility benefits linked to higher CV penetration, especially under high traffic
Raddaoui et al. (2020) [133]	Improve safety for large trucks in work zones using CV technology	Driving simulator experiment with 20 truck drivers under adverse weather conditions	Human subject experiment	CV-based warnings improve safety but multiple notifications can distract drivers
Ren et al. (2020) [137]	Enhance work zone safety and capacity using AI-based merge control	Cooperative driving model using reinforcement learning (SAC) in a fully automated environment	Simulation traffic data	AI-based merge control improves safety and mobility compared to traditional strategies
Wu et al. (2020) [188]	Evaluate CAV-based speed and lane-changing strategies in expressway work zones	Model predictive control for optimizing speed and lane-changing strategies	Simulation traffic data	Best strategies depend on traffic conditions; ELC+VSL best in heavy traffic with high CAV penetration
Mao et al. (2021) [97]	Compare safety of traditional DMS vs in-vehicle work zone warnings	Microsimulation comparing DMS and CV advisory systems	Simulation traffic data	CV warnings outperform DMS; optimal DMS placement depends on traffic conditions
Algomaiah and Li (2021) [6]	Analyze late merge strategies with and without CV technology	Microsimulation assessing throughput, delay, queue length and control variables	Simulation traffic data	CV-enabled late merge outperforms non-CV late merge, especially under moderate demand
Haque et al. (2023) [59]	Assess impact of platoons of connected heavy vehicles in work zones	Microsimulation calibrated to real work zone data	Empirical speed, volume, headway, and travel time data (Nebraska I-80 detectors + RITIS)	Increasing CAHV penetration improves safety and mobility in freeway work zones

1.3 Task 2: Identify Potential Work Zones

1.3.1 Introduction Building upon the literature review from the previous section, this chapter aims to identify potential freeway work zone segments and gather the necessary data for these segments. Due to the unavailability of freeway traffic flow data in North Carolina at the time of writing, we will utilize the California Department of Transportation (Caltrans) Performance Measurement System (PeMS) database to identify a potential freeway segment. A work zone will then be designed within this segment considering multiple configurations.

The structure of the following sections is as follows: Section 1.3.2 provides an overview of the Caltrans Performance Measurement System (PeMS). Section 1.3.3 outlines selected freeway segments and their associated data. Finally, Section 1.3.4 summarizes the key findings and conclusions of this chapter.

1.3.2 The Caltrans Performance Measurement System The California Department of Transportation (Caltrans) Performance Measurement System (PeMS) provides essential access to both real-time and historical performance data in various formats and presentation styles. It serves as a crucial tool for managers, engineers, planners, and researchers to comprehend transportation performance, identify issues, and devise effective solutions. PeMS enables a comprehensive assessment of freeway performance, facilitating informed operational decisions based on current network conditions. It analyzes congestion bottlenecks to recommend potential remedies and supports overall improved decision-making processes. The key features of PeMS can be summarized as follows:

- **Data Collection and Integration:** PeMS serves as the centralized repository for all of Caltrans' real-time traffic data, consolidating information from over 44,681 detectors reporting data every 30 seconds. It integrates data from Intelligent Transportation System (ITS) Vehicle Detector Stations (VDS), traffic counters, weight-in-motion (WIM) sensors, and other sources across California's state highways.
- **Analytical Capabilities:** As a real-time Archive Data Management System (rt-ADMS), PeMS collects, stores, and processes raw data to generate insights. It offers built-in analytical tools for computing standard transportation performance measures such as vehicle miles traveled (VMT), vehicle hours traveled (VHT), delay (in vehicle-hours), and level of service (LOS). These capabilities support various traffic analyses, including Highway Capacity Manual assessments, Synchro analyses, and simulations.
- **Data Accessibility and Use:** Users can query both current and archived freeway traffic data, generate summary reports on freeway conditions, and compute specialized performance measures like travel time reliability indices.
- **Support for Transportation Planning:** PeMS data is instrumental in completing Project Study Reports and other transportation planning documents, aiding model calibration, verifying study findings, and assessing traffic conditions for operational and capital improvements.

1.3.3 Identifying Potential Work Zones The area of interest is a particular segment of the I-5 freeway located in San Diego. This segment was selected for its strategic characteristics, including its minimal exposure to ramp-related traffic impacts, which ensures an environment conducive to studying freeway flow dynamics with minimal interruptions. This segment covers a total distance of about one mile (1.6 km), centered around postmile 26.64, and consists of a two-way interstate road with four lanes in each direction, each lane measuring 12 feet in width. The mainline speed limit for this section is set at 70 mph.

Additionally, the segment is equipped with vehicle detector stations and inductive loop detectors installed in each lane of the freeway. The purpose of these detectors is to collect, store, and process real-time traffic data continuously. The collected data is then transmitted to the Caltrans Performance Measurement System (PeMS) database for further analysis. The comprehensive data from these detectors allows for detailed monitoring and assessment of traffic patterns, congestion levels, and overall freeway performance under normal operating conditions. This setup ensures that the study can accurately capture the dynamics of freeway traffic flow with minimal external influences.

Given the study's focus on evaluating the effects of CAV technology within a work zone environment, the freeways data were specifically selected during periods where average speeds deviated moderately, approximately 15 miles per hour below the design speed limit. This deviation implies moderate traffic congestion prior to simulating a lane closure, thus offering a pertinent environment for examining the impacts of CAV technology. The study examined traffic patterns over a one-hour period during the morning peak, specifically from 8:15 AM to 9:15 AM, July 17, 2024. The traffic data has been aggregated to provide traffic volume and average speed in 5-minute intervals.

1.3.4 Summary This task focuses on selecting freeway segments suitable for simulating work zone scenarios and gathering necessary data. Leveraging the Caltrans Performance Measurement System (PeMS) database due to data limitations in North Carolina, the study identified strategic freeway segment based on its traffic characteristics and lane configurations. Detailed descriptions and field data from selected segments provide insights into traffic patterns and dynamics essential for evaluating future work zone impacts and Connected and Autonomous Vehicle (CAV) technology effects.

1.4 Task 3: Design Simulation Scenarios

1.4.1 Introduction Microscopic traffic simulation, such as VISSIM, and SUMO, have been extensively utilized in transportation planning, design, and evaluation due to their advantages of being cost-effective, risk-free, and time efficient. To enhance the reliability and validity of microscopic traffic simulation outcomes, the simulation scenario should closely replicate the characteristics of real-world traffic flow, such as traffic volume and speed. While most simulation platforms provide default parameter values intended to represent typical traffic flow characteristics, these predefined settings frequently fall short in capturing the complexities observed in real-world traffic environments. Thus, rigorous calibration of model parameters is essential. However, due to the high dimensionality and complexity of the parameter space, this task is often time-consuming and challenging. Besides, due to lack of gradient information, traditional mathematical programming methods are ineffective. Thus, this task employs metaheuristic approaches such as Genetic Algorithm (GA), Simulated Annealing (SA) and Particle Swarm Optimization (PSO) to find the optimal set of parameters so that minimize discrepancies between observed and simulated traffic data.

This task is organized as follows. Section 1.4.2 presents the configuration of work zone and basic settings in SUMO. Section 1.4.3 formulates the objective function employed in the calibration. Section 1.4.4 introduces the calibration process and three types of metaheuristic approaches. Section 1.4.5 describes the set of parameters in SUMO being calibrated. Section 1.4.6 presents the calibration results. Finally, Section 1.4.7 provides a comprehensive summary and concluding insights into the chapter.

1.4.2 Simulation Setup This study uses SUMO to conduct the calibration process. According to the collected data and the real-world freeway segmentation configuration, the traffic direction is from west to east, and the mainline section has 4 lanes. The speed limit for the mainline and work zone is 70 mph and 55 mph. Each simulation lasted for an hour of the a.m. peak, from 8:15 to 9:15 a.m. on July 17th, 2024. and the field traffic data (i.e. flow and speed) are aggregated into 5-min counts. The Wiedemann 99 car following model and the LC2013 lane-changing model are used.

1.4.3 Objective Function To minimize the difference between real word traffic conditions and simulated traffic conditions, the parameters of the microscopic traffic simulation model need to be calibrated. Specifically, the calibration process aims to minimize the differences between the observed and simulated traffic data, such as traffic volumes, speed, and travel time. In this study, the objective function uses the Mean Absolute Normalized Error (MANE), which has been widely used in parametric calibration functions.

1.4.4 Optimization Algorithms

1.4.4.1 Genetic Algorithm Genetic Algorithm (GA) is a heuristic optimization method based on the principles of natural selection and genetics [71]. Its basic principle is to simulate the process of biological evolution and optimize the solution space of the problem through selection, crossover and mutation. In the process of calibrating parameters of the car-following model, the genetic algorithm first randomly generates an initial population, in which each individual represents a combination of parameters, and each gene represents the parameter, and evaluates the individual's fitness through the objective function. An individual with high fitness will have a higher probability to participate in the reproduction process of the next generation. The selection operation picks individuals based on fitness. Then, the crossover operation simulates genetic recombination in nature, where the selected parent individuals exchange part of their genetic information to generate new offspring, thus exploring a wider solution space. To avoid the algorithm from falling into local optimal solutions, the mutation operation randomly changes some of the genes to increase the diversity of solutions. In each generation, the algorithm performs selection, crossover, and mutation operations through continuous iteration, and finally generates an individual with higher fitness as the optimal solution. The advantage of the genetic algorithm is that it does not rely on gradient information of the problem, and is suitable for solving complex, nonlinear optimization problems with strong global search capability [83, 196].

1.4.4.2 Simulated Annealing Simulated Annealing (SA) is a global optimization algorithm based on thermodynamic principles and is inspired by the energy evolution mechanism in the annealing process of metals.

When calibrating the parameters of the car-following model in SUMO, the simulated annealing algorithm optimizes the parameters by randomly perturbing the parameter combinations and deciding whether to update the current solution or not according to certain acceptance criteria. In this research, it minimizes the difference between the simulation results and the actual traffic flow data. First, the algorithm initializes a parameter combination as the current solution and sets the initial temperature, which determines the perturbation amplitude and acceptance probability during the search process. Subsequently, in each round of iterations, the algorithm randomly generates a new solution in the parameter space and calculates the corresponding fitness value of this solution. If the fitness of the new solution is better than the current one, it is accepted directly, otherwise the worse solution is accepted with a certain probability. By gradually decreasing the temperature, the simulated annealing algorithm can explore a wider solution space in the early stage to avoid falling to the local optimum. And it can gradually converge to the optimal parameter combination in the later stage, which makes the calibration results more accurately. The advantage of this algorithm is that it has strong search ability and can find better solutions in high-dimensional complex optimization problems. However, the convergence speed depends on the initial temperature, the cooling rate and the termination conditions [183].

1.4.4.3 Particle Swarm Optimization Particle Swarm Optimization (PSO) is an optimization algorithm based on group intelligence, which is inspired by the foraging behavior of bird flocks and the social behavior of fish swimming [24]. When calibrating the parameters of the car-following model in SUMO, the particle swarm algorithm can effectively search the solution space and optimize the model parameters to make the simulation results more compatible with the actual traffic flow data. In the process, a set of particles is first randomly generated in the parameter space, each particle represents a combination of parameters, and the simulation results (objective function value) are calculated according to this parameter combination. Each particle has its own position and velocity, the position represents the current value of the parameter, and the velocity indicates how to adjust the parameter. The particle adjusts its position during the search process based on its own historical best solution as well as the global best solution among all the particles, and the update formula for the velocity combines personal experience (i.e., the deviation of the particle from its own best position) and social experience (i.e., the deviation of the particle from the global best position). Through many iterations, the particle swarm gradually approaches the optimal parameter solution and finally finds the parameter combination that best matches the traffic flow observation data. For the calibration of the parameters of the car-follow model in SUMO, the particle swarm algorithm can effectively explore the multi-dimensional parameter space to find the optimal solution, thus improving the accuracy and reliability of the model [181].

1.4.5 SUMO Calibration Parameters Car-following models are a fundamental component of microscopic traffic simulation, representing how a vehicle adjusts its speed and acceleration based on the movement of a leading vehicle. The Wiedemann 99 model is a widely used psychophysical car-following model implemented in SUMO [11, 39]. As defined by Wiedemann 99 model, a vehicle has four primary driving states that describe different phases of interaction between the following vehicle and the lead vehicle [38]: (1) Free-Driving means that the leading vehicle is sufficiently far ahead, thus the following vehicle accelerates toward its desired speed without considering the leader's movement. (2) Approaching is defined as the following vehicle adjusting its speed when it perceives a speed difference with the lead vehicle. (3) Following means that the following vehicle maintains a steady speed while responding to small speed changes in the lead vehicle. (4) Braking is defined as the following vehicle applies emergency braking to avoid a collision. The Wiedemann 99 model can be calibrated by ten driving behavior parameters (i.e., CC0, CC1, . . . , CC9).

1.4.6 Calibration Results To ensure the algorithm's search ability in the solution space, the parameters in GA are repeated tests and the number of the crossover probability, mutation probability, population size, and generations were set at 0.9, 0.2, 20 and 20. The first iteration is the MANE value obtained using the default parameters. Under these default parameters, the MANE value is 19.2%, which means that the simulation environment does not reflect the real traffic conditions well. As the iteration progresses, the MANE value decreases and stabilizes at 12.3% at the 11th iteration. Similarly, after multiple tests, the parameters of the SA algorithm are set as follows: stopping temperature=1e-7; initial temperature=100; iterations=20; maximum stay counter=15. The MANE value decreases until it stabilized at 11.67% in the ninth generation. For PSO calibration process, at the beginning, the MANE value decreases rapidly, which reflects the global search capability of the PSO algorithm. The parameters of the PSO algorithm are set as follows: population size=20; maximum Iterations=20; weight=0.8; learning parameter 1=0.5; learning parameter 2=0.5. When iterating to 17 generations, the MANE value stabilizes at 11.38% and achieves the optimal result among the three algorithms. Therefore, we choose the results of PSO algorithms as the optimal parameters for the simulation environment.

1.4.7 Summary This chapter introduces the simulation settings, calibration process of the microscopic simulation model and three types of optimization algorithms. A comparative analysis of the calibration results for the three algorithms reveals that the parameters optimized through PSO demonstrate superior performance, achieving a MANE value of 11.38%, which is notably better than the default parameters, which resulted in a MANE value of 19.2%. Although we tried several experiments without obtaining better results than the current one, there is still space for improvement in the current optimization strategy. For example, some emerging optimization algorithms, such as the Grey Wolf Optimizer and Whale Optimization Algorithm, or warm-start methods that use solutions obtained from one algorithm as starting points for another, may get better solutions. In the future, we will further investigate these issues.

1.5 Task 4: Evaluate the Impact of CAVs on Work Zones Performances

1.5.1 Introduction This task presents the numerical results obtained from the simulations conducted in this study. The analysis considers three types of vehicles: Human-Driven Vehicles (HDVs), Autonomous Vehicles (AVs), and Connected and Autonomous Vehicles (CAVs). To accurately represent their driving behavior, different car-following models were employed. The calibrated Wiedemann 99 model was used for HDVs, the Intelligent Driver Model (IDM) was applied to AVs, and the Cooperative Adaptive Cruise Control (CACC) model was implemented for CAVs. Two primary lane-reduction scenarios were examined, consisting of a single-lane drop and a dual-lane drop. The impact of AV and CAV integration on freeway operations was evaluated under varying market penetration rates and traffic demand levels, with particular attention to safety, mobility, and environmental performance.

1.5.2 Numerical Results Building upon the potential freeway segments identified in Task 2, a four-lane (unidirectional) freeway segment was selected from the Caltrans Performance Measurement System (PeMS) for detailed analysis. This segment was selected due to its suitability for evaluating the effects of multi-lane drop scenarios. Three distinct traffic demand levels were defined for the simulation: low demand, representing the minimum observed hourly traffic volume during the day; high demand, corresponding to the peak hourly volume; and medium demand, calculated as the median value between the low and high demand levels. The impact of AVs and CAVs on the selected segment is assessed across a range of market penetration rates. The corresponding numerical results are presented and discussed in the subsequent sections.

1.5.2.1 Single Lane Drop

1.5.2.1.1 Low Demand As outlined previously, simulation metrics related to safety (Time-to-Collision ¡ 3.0 seconds), mobility (work zone throughput and average speed), and environmental performance (greenhouse gas emissions and air pollutant levels) were collected at each simulation step. In addition, the percentage change in each metric relative to a baseline scenario consisting of 100% human-driven vehicles were presented in parentheses. Analyses were conducted across a range of AV and CAV market penetration rates, increasing in 10% increments. The empirical traffic demand corresponding to this scenario is 4,676 vehicles per hour. For the safety-related metric under different penetration level of CAVs and AVs, the Time-to-Collision (TTC) metric improves by only 6.8% relative to the baseline in a fully CAV environment. In contrast, a fully AV environment results in a more pronounced improvement, with TTC decreasing by 34%. The simulation results suggest that the benefits of CAVs are limited under low-demand conditions. This outcome can be attributed to the absence of significant congestion, which reduces the operational advantages typically offered by advanced vehicle technologies. Mobility-related metrics, including work zone throughput and mean speed, show minimal variation across the different vehicle technologies. Specifically, the mean speed remains within a 4% deviation from the fully human-driven baseline, while work zone throughput fluctuates by no more than 0.05% across scenarios involving HDVs, AVs, and CAVs. In contrast, the impacts of CAV and AV on environmental metrics are more substantial. A fully AV environment yields a 22% reduction in greenhouse gas (GHG) emissions, specifically in carbon dioxide (CO_2) and carbon monoxide (CO), while a 100% CAV scenario results in a 17.3% reduction. Similarly, fully AV and fully CAV environments yield reductions in air pollutants by 30% and 22.55%, respectively. These findings underscore the environmental advantages of AV and CAV technologies, even in conditions where their contributions to safety and mobility are comparatively limited.

1.5.2.1.2 Medium Demand To enhance the robustness of the analysis, additional simulations were conducted under a medium-demand condition. This scenario was defined as the median of the empirically observed high- and low-demand levels, corresponding to an input volume of 6,014 vehicles per hour. The simulation results indicate that safety benefits become more pronounced at this intermediate demand level. In particular, the Time-to-Collision (TTC) metric shows a relatively consistent and progressive reduction with increasing market penetration of AVs and CAVs. Under full adoption, a 100% AV environment reduces TTC by 86%, while a fully CAV environment achieves a 54% reduction compared to the baseline of human-driven vehicles. Mobility metrics remain relatively stable across all scenarios. Work zone throughput, in particular, exhibits less than a 1% deviation from the human-driven baseline, suggesting that the medium demand level does not induce significant congestion or operational delays.Consistent with findings from the low-demand scenario, environmental benefits are substantial. Greenhouse gas (GHG) emissions are reduced by 48% in a fully AV environment and by 43% in a fully CAV environment. Similarly, air pollution levels decline by 58% and 51% for fully AV and CAV scenarios, respectively. These results reinforce the potential of AVs and CAVs to contribute meaningfully to safety and environmental sustainability, even in the absence of major mobility improvements.

1.5.2.1.3 High Demand Traffic volume was increased to the highest observed demand level for the study day, corresponding to an input value of 7,352 vehicles per hour in the SUMO simulation. Under this high-demand condition, CAVs exhibited superior overall performance. In terms of safety, surrogate conflict counts based on Time-to-Collision (TTC) metrics were reduced by 12% in a fully AV environment and by 63% in a fully CAV environment, indicating the added benefit of vehicle connectivity in mitigating crash risk. According to the results, work zone throughput increased under both deployment scenarios, with AVs producing a 19% improvement and CAVs yielding an 18% increase. Despite the similar gains in throughput, notable differences were observed in mean travel speeds. In addition, AVs improved average speeds by 20%, whereas CAVs achieved a 70% increase. Speed was measured immediately downstream of the work zone using the same virtual detector employed for throughput analysis. This location reflects how efficiently traffic disperses after navigating the bottleneck. The substantial speed improvement in the CAV scenario, despite similar throughput, suggests more stable flow conditions and faster post-bottleneck recovery. In addition, the observed difference reflects the persistence of congestion and turbulence in non-connected environments. CAVs likely mitigated this effect through vehicle coordination, reduced reaction time variability, and anticipatory deceleration, which collectively helped suppress traffic shockwaves and improve dispersal efficiency. Following a similar trend, emissions metrics also showed substantial improvement, with CAVs outperforming AVs in reducing environmental impact. In a fully CAV environment, greenhouse gas (GHG) emissions were reduced by 56%, while a fully AV environment achieved a 37% reduction. These reductions reflect improvements not only for the automated vehicle fleets but also for surrounding human-driven vehicles, due to smoother traffic flow and decreased idling. In parallel, air pollutant emissions such as nitrogen oxides (NO_x) and particulate matter (PM) also declined, with reductions of 63% in the fully CAV scenario and 40% in the fully AV scenario. These findings reinforce the broader sustainability potential of CAV technology, which combines improvements in safety and mobility with meaningful reductions in environmental impact.

1.5.2.2 Dual Lane Drops

1.5.2.2.1 Low Demand In this scenario, an additional lane was closed, resulting in a dual-lane drop work zone configuration. All other simulation parameters, including speed limits, traffic demand, and market penetration rates, remained consistent with the single-lane drop scenario. Even under low-demand conditions, the dual lane drop configuration led to noticeably more complex traffic dynamics due to increased lane-changing activity and reduced roadway capacity. These intensified conditions allowed the benefits of CAVs to become more evident. Compared to both AVs and HDVs, CAVs demonstrated substantially superior performance across safety, mobility, and environmental metrics. Safety performance, as measured by the Time-to-Collision (TTC) metric, showed a marked improvement in a fully CAV environment, with TTC decreasing by 71% relative to the fully human-driven baseline. By contrast, the fully AV environment experienced a 6% increase in critical TTC occurrences, suggesting a slight deterioration in safety under these conditions. This may be attributed to the limited adaptability of AVs in managing the increased turbulence associated with extensive lane closures. Mobility metrics also improved under automated and connected scenarios. In a fully CAV environment, the mean speed increased by 78%, rising from 34 miles per hour to 60 miles per hour. Work zone throughput also increased, with improvements of 8.8% for CAVs and 8.6% for AVs, relative to the baseline. The modest throughput gains should be interpreted in the context of fixed demand levels. Since the number of vehicles in the network remained constant, improvements in speed and throughput reflect the ability of CAVs and AVs to reduce congestion and flow disruptions, rather than a true expansion of capacity. Environmental performance exhibited the most significant gains. In a fully AV environment, greenhouse gas (GHG) emissions, specifically carbon dioxide (CO_2) and carbon monoxide (CO), were reduced by 32%. In the fully CAV environment, emissions declined by 53%. Similarly, air pollutant emissions such as nitrogen oxides (NO_x) and particulate matter (PM) were reduced by 34% in the AV scenario and by 59% in the CAV scenario. These substantial reductions are closely tied to smoother vehicle trajectories, fewer stop-and-go cycles, and improved flow stability. Although demand remained fixed, the enhanced operational efficiency of connected and automated vehicles contributed meaningfully to both emissions and air quality outcomes. These findings highlight the potential of CAVs not only to improve safety and mobility, but also to advance sustainability objectives, particularly in complex traffic conditions involving multiple lane closures.

1.5.2.2.2 Medium Demand The medium-demand scenario was defined as the median between the empirically observed high and low traffic volumes and corresponds to an input value of 6,014 vehicles per hour. All simulation parameters remained consistent with previous scenarios, including roadway geometry, vehicle behavior models, and market penetration rates. This scenario introduces a more congested traffic environment compared to the low-demand case, allowing for a more nuanced evaluation of vehicle technology performance under moderate stress conditions. The dual-lane drop configuration under medium demand further emphasized the distinctions between AVs and CAVs. In particular, safety outcomes diverged significantly across vehicle types. In the fully CAV environment, the Time-to-Collision (TTC) metric decreased by 63.4%, indicating a substantial reduction in surrogate conflicts relative to the baseline. Conversely, in the fully AV scenario, TTC increased by 48%, suggesting a deterioration in safety performance. This adverse outcome may reflect the limitations of non-cooperative AV behavior in responding to increased merging activity and lateral disturbances common to dual-lane drop conditions at medium demand levels. Mobility performance also varied considerably. In a fully CAV environment, the mean speed nearly doubled, increasing by 96.2%, while work zone throughput improved by 31.3%. These results suggest that CAVs were highly effective in stabilizing flow, reducing shockwave formation, and enhancing post-bottleneck recovery. In contrast, the fully AV environment exhibited a 14% reduction in mean speed, though throughput still improved by 13.7%. This indicates that AVs were able to maintain vehicle throughput but did so at the expense of flow quality and travel efficiency. As with previous scenarios, it is important to note that these results were derived from a one-hour simulation period under fixed demand conditions. Throughput gains, therefore, reflect reduced congestion and improved flow reliability, rather than an increase in absolute capacity. Environmental performance metrics further reinforced the superior performance of CAVs. In the fully CAV environment, greenhouse gas (GHG) emissions were reduced by 51.3%, while the AV scenario achieved a more modest 12.1% reduction. Similarly, air pollutant emissions, including nitrogen oxides (NO_x) and particulate matter (PM), declined by 58.5% in the CAV scenario and by 9% in the AV scenario. These reductions can be attributed to smoother vehicle trajectories, reduced stop-and-go behavior, and fewer abrupt acceleration and deceleration events. Although demand remained constant, the enhanced operational efficiency of CAVs delivered significant environmental benefits. Overall, the medium-demand dual-lane drop scenario highlights the limitations of AVs in managing increasingly complex traffic conditions in the absence of vehicle-to-vehicle coordination. In contrast, CAVs consistently demonstrated superior performance across all evaluated dimensions, including safety, mobility, and environmental sustainability.

1.5.2.2.3 High Demand The high-demand scenario represents the most congested traffic condition evaluated in this study and corresponds to the peak observed traffic volume of 7,352 vehicles per hour. As in previous scenarios, the dual-lane drop configuration was applied, and all other simulation parameters, including vehicle behavior models and market penetration rates, were held constant. Under these high-demand conditions, the distinctions between AVs and CAVs became even more pronounced. Safety outcomes, measured via the Time-to-Collision (TTC) metric, deteriorated substantially in the fully AV environment, where TTC increased by 50.52% compared to the human-driven baseline. This result highlights the limited capacity of non-cooperative AVs to manage complex interactions in heavily congested environments. In contrast, the fully CAV scenario yielded a 47.66% reduction in TTC, indicating a significant improvement in safety. However, a slight increase in conflict risk was observed at lower CAV market penetration rates (e.g., 10% and 20%), likely due to the behavioral discontinuity between connected and non-connected vehicles within the mixed traffic stream. Mobility metrics revealed a similar contrast in performance. In the fully CAV environment, mean speed increased by 60.5%, reaching 42.33 miles per hour compared to the 26.70 mph baseline. In contrast, the fully AV scenario experienced a 10.26% reduction in mean speed, dropping to 23.96 mph. Work zone throughput also increased for both AVs and CAVs, with gains of 33.1% and 47.1%, respectively. These results indicate that while AVs were able to improve throughput, they did so at the expense of flow quality and vehicle spacing, resulting in degraded safety and mobility. CAVs, on the other hand, effectively coordinated movement across vehicles, improving both flow efficiency and operational stability. Environmental performance followed the same trend. Greenhouse gas (GHG) emissions, including carbon dioxide (CO_2) and carbon monoxide (CO), decreased by 10.34% in the AV scenario and by 42.63% in the CAV scenario. Similarly, air pollutant emissions such as nitrogen oxides (NO_x) and particulate matter (PM) declined by 6.75% in the AV environment and by 50% under full CAV deployment. These reductions are attributable to the smoother trajectories, reduced idling, and less aggressive acceleration behavior enabled by cooperative vehicle operation. Overall, the high-demand dual-lane drop scenario highlights the limitations of AV technology in the absence of connectivity and cooperation. While AVs provide moderate improvements in throughput and emissions, they struggle to manage complex safety interactions and exhibit limited gains in speed and flow reliability. In contrast, CAVs deliver consistent and substantial benefits across all performance metrics, underscoring their value in high-density, high-complexity freeway environments.

1.5.3 Summary This section presents the simulation results for freeway work zone scenarios involving both single-lane and dual-lane drops under varying traffic demand levels. The analysis evaluates the performance of AVs and CAVs in terms of safety, mobility, and environmental impact. Across all scenarios, CAVs consistently showed more favorable outcomes, particularly as work zone conditions became more constrained and traffic demand increased. While AVs contributed to improvements in certain areas, they were less effective in maintaining flow stability and managing conflicts in more complex environments. These findings underscore the growing relevance of vehicle connectivity in supporting safe and efficient operations within freeway work zones.

1.6 Task 5: Develop Guidelines Considering Different Levels of CAV Market Penetration

1.6.1 Introduction Connected and Automated Vehicle (CAV) technologies integrate the capabilities of connected vehicles (CV) and automated vehicles (AV), offering a powerful combination of communication and autonomous driving features. By leveraging the strengths of both technologies, CAVs have the potential to significantly revolutionize transportation systems by improving safety, enhancing mobility, and contributing to environmental sustainability goals. However, due to the increasing demand for pavement maintenance and upgrades to preserve an acceptable level of service, work zone activities will remain a critical and frequent necessity. Work zones, in turn, can severely impact roadway safety, reduce operational efficiency and capacity, and contribute to negative environmental consequences both locally and globally. Addressing these work zone-induced challenges demands substantial investments in cutting-edge technologies and intelligent transportation systems to mitigate their adverse effects. As CAVs increasingly become part of the transportation ecosystem, their interaction with work zones becomes inevitable. Understanding and optimizing this interaction is essential, as CAVs have the potential to improve traffic flow and safety within these disruptive zones. Given the expected rise in CAV market penetration, evaluating their role in mitigating work zone challenges is a timely and necessary area of research with significant implications for future transportation planning and policy. The main objective of this project was to evaluate the potential impact of Connected and Automated Vehicles (CAVs) on work zone safety, operational efficiency, and environmental outcomes, across different levels of sensitivity related to traffic demand and varying vehicle compositions. Using the Simulation of Urban Mobility (SUMO) microsimulation platform, a representative freeway segment prone to work zone activity was identified through the Caltrans Performance Measurement System (PeMS) database. To ensure realistic modeling, various metaheuristic algorithms were employed to calibrate car-following parameters based on observed traffic behavior under human-driven conditions. Following calibration, simulations were conducted under multiple scenarios featuring different market penetration rates of (AVs) and CAVs and work zone configurations. Simulation results were analyzed in detail to understand the effects on traffic flow, safety, and emissions. Overall, the findings of this study provide valuable insights for traffic engineers, planners, and stakeholders by illustrating how varying levels CAV adoption could influence freeway work zone performance and contribute toward achieving broader safety, mobility, and environmental sustainability goals. These insights can ultimately support improved traffic management strategies in work zone settings.

1.6.2 Summary and Conclusions Through a comprehensive review of the current state-of-the-art and state-of-the-practice of CAV technologies around work zones, various methodological approaches to integrated CAV technologies (mostly CV and AV technologies) in work zone environment are summarized. Simulation-based method has been widely used in CAV related studies. Compared to other approaches, simulation-based method is imperative for practical decision making in transportation planning and operations. To conduct analysis using microsimulation models, potential scenarios need to be selected. Given the challenges associated with obtaining comprehensive work zone traffic data, this study utilized the Caltrans Performance Measurement System (PeMS) as the primary data source. PeMS is a web-based platform that provides users with real-time and historical traffic data, including speed, flow, capacity, and delay metrics. By leveraging PeMS, researchers can access detailed information on freeway segments, identify congestion bottlenecks, evaluate freeway performance, and inform operational decision-making. In this study, a four-lane (one direction) freeway segment was selected from PeMS. The site was chosen based on its minimal ramp interference and moderate baseline congestion, providing a stable scenario before simulating lane drops to introduce work zone conditions. Traffic simulation serves as a fundamental tool in transportation planning due to its cost-effectiveness, scalability, and proven ability to replicate complex traffic dynamics. In this study, the microscopic traffic simulation software Simulation of Urban Mobility (SUMO) was employed to model traffic operations throughout the analysis. To accurately replicate the real-world traffic flow and speed patterns observed in the PeMS data, three metaheuristic algorithms were implemented to calibrate the simulation: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA). Each algorithm was independently evaluated with the objective of minimizing the discrepancy between observed traffic conditions and simulated outputs. Although the algorithms are inherently different in their optimization approaches, the study prioritized obtaining the most accurate calibration results rather than comparing algorithmic performance. Among the three, the PSO algorithm achieved the best calibration results, yielding an accuracy of 11.38%, which is notably better than the default parameters (19.2%). After completing the calibration, single- and double-lane drop scenarios were introduced into the freeway segment. For each scenario, different market penetration rates of AVs and CAVs were tested under varying traffic demand levels. These demand levels included low traffic (observed from the collected data), medium traffic (defined as the median value between low and high demand), and high traffic (selected from peak observed values). Different mixtures of vehicle types were introduced, and key performance metrics related to safety (Time-to-Collision, TTC), mobility (work zone throughput and mean speed), and environmental impact (air pollution and greenhouse gas emissions) were collected for each scenario. The findings suggest that the impact of CAVs is often minimal under low traffic intensity, particularly in relation to lane closures and demand levels. However, as traffic conditions become more intense, the benefits of CAV deployment become increasingly evident. Connected and Autonomous Vehicles (CAVs) consistently demonstrated superior performance across safety, mobility, and environmental metrics compared to Human-Driven Vehicles (HDVs) and standalone Autonomous Vehicles (AVs) in multiple freeway work zone scenarios. Under low-demand conditions, the benefits of CAVs were relatively modest, given the absence of significant congestion. However, as traffic demand increased, CAVs substantially reduced surrogate crash conflicts, improved mean speeds, and decreased greenhouse gas emissions and air pollution metrics. For instance, under high-demand single-lane drop scenarios, CAVs reduced critical Time-to-Collision (TTC) events by 63%, increased downstream mean speeds by up to 70%, and achieved a 56% reduction in greenhouse gas emissions. These improvements are largely attributed to CAVs' ability to coordinate vehicle movements, smooth traffic flows, and mitigate shockwave effects, advantages that AVs without connectivity could not replicate at the same level. Under more complex dual-lane drop conditions, the advantages of CAVs became even more pronounced. While AVs sometimes worsened safety by failing to adapt to high merging activity, CAVs effectively stabilized flow, doubled mean speeds, and provided substantial environmental benefits, including up to a 59% reduction in air pollutant emissions under high-demand conditions. Even in highly congested environments, CAVs maintained operational stability and reduced crash risk, emphasizing that connectivity is crucial for managing complex freeway scenarios. Overall, the study clearly indicates that while AVs alone offer limited and sometimes inconsistent benefits, the integration of connectivity through CAV systems yields significant improvements across all critical dimensions, making CAVs essential for future freeway traffic management.

1.6.3 Direction for Future Research While this study offers several useful findings, there are areas for improvement that future research could address. The work zones evaluated in this study were limited to basic freeway segments. Future studies could expand the scope to more complex scenarios such as merging areas, diverging segments, or freeway weaving sections. Additionally, the calibration process in this study relied on metaheuristic approaches, which, while effective, could be further enhanced. Future research could incorporate artificial intelligence-based optimization techniques to improve calibration accuracy and robustness. Extending the calibration process to include other car-following models would also provide a more comprehensive analysis. Beyond freeways, future studies could investigate the impact of CAVs on work zones along arterial roadways, where different traffic dynamics and control measures may present unique challenges and opportunities.

1.7 Relevance to NCDOT

The report will help NCDOT by: (1) Using simulation insights to optimize lane closures under different traffic conditions and at different levels of market penetration rates to improve safety, minimize congestion and emission in the state of North Carolina. (2) Understanding the role of metaheuristic algorithms in designing simulations that accurately replicate the prevailing traffic condition for planning purposes (and are also transferable). (3) Reinforcing the role of connectivity as a differentiator enabling AVs to stabilize traffic and improve safety (standalone AVs are less effective in complex zones) and quantifying potential benefits of providing investments in V2X technology. (4) Methodologies developed can be extended to more complex environments, such as weaving segments and innovative interchanges.

Chapter 2 : Research Findings under Project 5: Evaluating Connected and Secure Edge Infrastructure for Scalable Hardware-in-the-Loop CAV Testbeds

2.1 Background

Connected and Autonomous Vehicles (CAVs) are emerging as a foundational element of next-generation Intelligent Transportation Systems (ITS), offering the potential to improve safety, mobility, and operational efficiency across transportation networks. However, realizing these benefits at scale requires communication and computing infrastructure capable of supporting ultra-low-latency data exchange, scalable data processing, and reliable coordination between vehicles and roadside systems. Traditional centralized cloud architectures alone cannot satisfy the stringent latency and reliability requirements of real-time vehicular applications such as cooperative perception, collision avoidance, and coordinated maneuvering. These constraints have motivated the adoption of vehicular edge computing and distributed networking architectures that bring computation and decision-making closer to the point of data generation.

The expansion of CAV deployments simultaneously introduces significant cybersecurity exposure across multiple layers of the transportation ecosystem. Roadside units (RSUs), wireless Vehicle-to-Everything (V2X) communication channels, in-vehicle networks, and backend traffic management systems all exchange safety-critical information that must remain trustworthy and accurate. Many field devices operate in heterogeneous, multi-vendor environments and coexist with legacy systems lacking modern cybersecurity protections. National frameworks—including the NIST Cybersecurity Framework 2.0, ISO/SAE 21434, and UNECE Regulation No. 155—establish lifecycle risk management expectations but provide limited prescriptive guidance for implementing scalable, real-time intrusion detection across distributed and resource-constrained CAV infrastructure. Effective cybersecurity therefore requires detection and response mechanisms that operate within device-level resource constraints, maintain resilience in the presence of compromised components, and coordinate across assets owned by different parties.

Complementing these infrastructure and security challenges, Digital Twin (DT) technology has emerged as a promising paradigm for bridging the gap between physical transportation assets and computational intelligence. By coupling physical vehicles and infrastructure with virtual counterparts through continuous real-time synchronization, Digital Twin architectures support monitoring, predictive analytics, scenario-based analysis, and adaptive control in CAV environments. Maintaining high-fidelity Digital Twins under data-intensive, real-time conditions requires intelligent resource provisioning across distributed edge and cloud computing systems—a problem that grows in complexity as the number of connected vehicles increases.

Despite progress in each of these domains individually, significant gaps remain in evaluating how edge computing, Digital Twin synchronization, and cybersecurity detection interact within an integrated, hardware-grounded testbed environment representative of real-world deployment conditions. Most existing evaluations rely on purely simulated configurations that do not capture the resource constraints, communication variability, and multi-vendor heterogeneity characteristic of field infrastructure. This project addressed these gaps through a collaborative effort between North Carolina Agricultural and Technical State University (NCA&T) and North Carolina State University (NCSU), organized around two primary objectives: (1) develop and test a connected and secure edge architecture based on a Cellular Vehicle-to-Everything (C-V2X) Digital Twin, and (2) recommend program enhancements to advance North Carolina's readiness for scalable and secure CAV communication infrastructure. The following sections present the research findings across four task areas: hardware-in-the-loop evaluation of a Software-Defined Vehicular Edge Computing (SDVEC) [86] platform with intelligent traffic classification and Quality-of-Service provisioning (Task 2); establishment of a C-V2X Digital Twin with learning-based edge resource provisioning (Task 3); evaluation of a federated intrusion detection framework for distributed CAV cybersecurity (Task 4); and synthesis of program enhancement recommendations for the North Carolina Department of Transportation (Task 5).

2.2 Task 1: Literature Review

This section reviews the literature relevant to the research conducted in this project. The review covers simulation-based validation of autonomous vehicle systems, Digital Twin frameworks for Connected and Autonomous Vehicle (CAV) development, communication and computing challenges underlying vehicular Digital Twin deployments, and cybersecurity for CAV roadside infrastructure. Together, these bodies of work establish the technical foundation and identify the gaps that motivate the research tasks described in subsequent sections.

Simulation-based validation enables safe, repeatable evaluation of autonomous vehicle systems prior to real-world deployment. Szalay [155] presents a next-generation X-in-the-loop simulation (XILS) methodology that combines real hardware, software, and virtual models within a unified testing framework. Beyond enabling reproducible scenario execution, the work introduces a structured reliability evaluation approach based on scenario definition, key parameter selection, and statistical comparison between XILS and real-world test data, thereby quantifying the trustworthiness of simulation-derived results. Cime et al. [31] integrate Hardware-in-the-Loop (HiL), Traffic-in-the-Loop (TiL), and Software-in-the-Loop (SiL) into a single platform that captures the ego vehicle, surrounding traffic behavior, traffic density, routing, signal timing, and the penetration of autonomous and ride-hailing vehicles in geo-fenced urban areas. The platform further incorporates Vehicle-to-Everything (V2X) capability through an external Python library, though the authors acknowledge limitations in generating realistic maps, modeling vegetation, and accurately representing sensor constraints. Chen et al. [29] propose a vehicle-in-the-loop (ViL) method that introduces a real autonomous vehicle and real sensors into the loop alongside configurable virtual scenarios. Their approach delivers virtual perception results directly to the vehicle in a unified fusion data format, reducing computational overhead, and employs OSM-based high-definition maps to decouple scenario design from a specific physical test site. Across these studies, the gap between simulated and real-world behavior remains a persistent challenge, underscoring the need for Digital Twin approaches that can maintain continuously synchronized representations of both the vehicle and its operating environment.

Digital Twin (DT) methods extend the simulation paradigm by establishing persistent, bidirectional computational representations that support not only testing but also real-time monitoring and operational decision-making throughout the vehicle lifecycle. Wang et al. [186] present a DT approach in which onboard sensor data are transmitted to a cloud server via vehicle-to-cloud (V2C) communication over a cellular network. The server constructs a virtual representation, processes the data, and returns results to the vehicle, enabling drivers to benefit from an Advanced Driver Assistance System (ADAS) with all processing carried out in the cloud. Salehi et al. [141] introduce a systems engineering approach for autonomous driving based on the Munich Agile Concept for a DT system. Their method organizes the development process through a six-level hierarchy—System Requirement, System Functional, System Architecture, System Validation, System Test, and System-Usage-Level—with the first three levels defined using the Systems Modelling Language (SysML). Culley et al. [32] develop an autonomous driving system using a minimal sensor suite and affordable processing hardware, achieving 25 fps object detection at 92% mean average precision. The authors also provide an open-source real-time simulation tool that mirrors the physical vehicle and its sensors, and a design study confirms that the simulator enables effective tuning of control parameters. While these DT frameworks demonstrate clear value for vehicle development and monitoring, their practical deployment depends on the underlying communication and computing infrastructure that sustains real-time data exchange and model synchronization.

Realizing DT capabilities in vehicular environments requires communication and computing resources that can meet the data exchange, processing, and synchronization demands of maintaining real-time digital replicas. Zhang et al. [210] propose a two-stage resource scheduling method for converged communication and computing networks that handles resource coordination and transmission scheduling online, adapting to varying computing resources and time-slot availability. However, the greedy scheduling methods commonly used in this domain do not address the synchronization requirements critical to DT systems. Yang et al. [193] address latency in vehicular edge computing caused by sub-task dependencies and uneven workload distribution across Mobile Edge Computing (MEC) servers. Their joint computation offloading and resource allocation method combines particle swarm optimization and genetic algorithms to optimize task offloading, resource allocation, and load balancing. While results show improvement at the tested scale, the study does not evaluate performance under substantially larger vehicular networks or heavier task loads. These unresolved communication and computing challenges have direct implications for cybersecurity, because the same networked infrastructure that enables DT synchronization and V2X cooperation also introduces attack surfaces that must be secured.

Deployment of CAV roadside infrastructure across U.S. corridors has expanded through the USDOT Connected Vehicle Pilot and related state DOT installations of Roadside Units (RSUs) and connected signal systems, creating operational communication paths among vehicles, RSUs, traffic signal controllers, and Traffic Management Centers (TMCs). FHWA notes that TMC and Intelligent Transportation System (ITS) field deployments rely on IP-enabled networks and wireless connectivity and that these devices no longer function as closed systems, expanding exposure to cyber threats [168]. NHTSA emphasizes that modern vehicle platforms incorporate externally reachable interfaces—including telematics units, V2X radios, and diagnostic services—requiring lifecycle cybersecurity controls

[112]. The cybersecurity requirements governing these systems are shaped by several frameworks. NHTSA's *Cybersecurity Best Practices for the Safety of Modern Vehicles* treats monitoring, incident response, and coordinated vulnerability disclosure as lifecycle activities [112]. NIST Cybersecurity Framework 2.0 organizes cybersecurity around six functions, adds an explicit Govern function, and links Detect and Respond outcomes to organizational oversight [124]. ISO/SAE 21434 operationalizes threat analysis and risk assessment within engineering workflows and ties security requirements to verification and post-deployment monitoring [1]. UNECE Regulation No. 155 requires a cybersecurity management system for type approval that includes monitoring and response processes for evolving threats [175]. These frameworks define what must be achieved but leave key engineering decisions open, including where telemetry is collected, what signals are sufficient for detection, and how detection performance is evaluated across distributed field devices.

The engineering decisions left open by these frameworks must contend with cyber risk that concentrates at three technical surfaces. The Controller Area Network (CAN) bus, a common in-vehicle communication backbone, lacks message encryption and sender authentication, leaving receivers exposed to injected frames that are syntactically valid at the bus level [154]. Wireless V2X introduces a second surface because broadcast authenticity does not ensure message correctness, motivating misbehavior detection methods based on plausibility checks and physical-process constraints [178]. A third surface arises at roadside components; Petit and Shladover [127] analyze cyberattack vectors against automated-vehicle-related systems and emphasize that external interfaces and supporting infrastructure can be leveraged to influence vehicle behavior.

To address these attack surfaces, intrusion detection in vehicular networks has developed along three principal approaches: signature-based matching against stored attack patterns, anomaly-based deviation from a learned baseline, and specification-based deviation from a defined behavioral model [37]. Signature-based detectors perform well on known attack instances but do not cover novel variants or zero-day behaviors. Anomaly-based detectors can expose previously unseen attacks but are sensitive to baseline drift and profile quality. Specification-based detectors encode expected protocol or timing behavior directly; Olufowobi et al. [123] introduced SAIDuCANT, which extracts a real-time timing model for CAN traffic and reports low false positives. Hanselmann et al. [58] proposed CANet, an anomaly-based approach achieving true negative rates typically above 0.99 while detecting replay-style anomalies. Where these conventional approaches face limitations—particularly in handling high-dimensional data structure and temporal dependencies spanning multiple message intervals—learning-based detectors offer an alternative. Tanksale [159] models normal CAN traffic as a time series using an LSTM predictor designed for low-resource deployment on in-vehicle Electronic Control Units (ECUs). Song, Woo, and Kim [154] train a deep convolutional network for CAN intrusion detection and report strong classification performance across multiple attack types. Jeong et al. [67] target automotive Ethernet AVTP stream injection, reporting detection performance and measured inference time on embedded hardware including Jetson TX2 with a real-time feasibility argument tied to packet generation intervals. In V2X settings, Tsukada et al. [171] evaluate misbehavior detection using observations shared among vehicles, which improves detection of falsified messages but introduces dependence on the availability and timeliness of exchanged data.

A practical limitation shared by many of the detection methods described above is their reliance on centralized telemetry collection for model updates and triage—an assumption that transportation deployments make fragile due to multi-organizational data ownership and privacy constraints. Federated learning addresses this by keeping data local while exchanging model parameters. Thein et al. [165] train locally and exchange parameters to reduce transmission cost and privacy risk, and further propose a server-side cosine-similarity mechanism to mitigate poisoning attacks from malicious client updates. Liu et al. [90] evaluate federated IDS under non-IID data conditions and propose a rebalancing method validated on UNSW-NB15. Even when detection is effective, translating detection scores into operational risk reduction depends on enforcement speed. Luo et al. [92] report per-packet detection time on embedded hardware (Jetson Xavier NX) and link real-time suitability to whether the IDS can match the packet rate on the monitored link. Even with fast inference, mitigation introduces additional delay depending on where filtering is enforced and how quickly rules are activated. For V2X misbehavior, response depends on reporting and revocation pipelines rather than local filtering alone; the C2C-CC misbehavior detection white paper describes forwarding detection outputs to a Misbehavior Authority for coordination with revocation processes [27]. U.S. SCMS documentation treats revocation as an infrastructure process with certificate lifecycle and distribution considerations that must accommodate devices with intermittent connectivity [75].

Despite the progress described above, public ITS and CAV-supporting deployments introduce practical constraints that current detection evaluations often leave unmeasured. Field devices span multiple vendors and firmware baselines, making patch cadence and configuration consistency uneven. On-device limits in CPU, memory, and storage bound feasible feature extraction, model capacity, and refresh frequency. Variable backhaul latency and intermittent connectivity affect what can be synchronized across RSUs and what must be decided locally. Many evaluations rely on controlled traces under fixed configurations, so reported accuracy may mask sensitivity to firmware revisions, sensor drift, and background traffic variation. A deployment-relevant evidence base requires measurements that pair detection quality with compute cost, update traffic, and enforcement delay under conditions that resemble field operations.

In summary, the literature establishes that simulation-based validation has advanced toward integrated mixed-reality environments, yet the fidelity gap between simulated and real-world conditions persists. Digital Twin frameworks provide persistent computational representations that support the vehicle lifecycle from design through operation, but their effectiveness depends on communication and computing infrastructure whose resource scheduling and synchronization challenges remain incompletely resolved at scale. The cybersecurity literature has produced detection methods spanning signature-based, anomaly-based, specification-based, and learning-based categories, along with distributed learning approaches that address data locality constraints, but critical gaps remain in evaluating these methods under deployment-realistic conditions—including on-device resource limits, heterogeneous firmware environments, intermittent backhaul, and end-to-end enforcement delay. These gaps collectively define the research space that the subsequent sections of this report address through the project's simulation, Digital Twin, and cybersecurity tasks.

2.3 Task 2: A Hardware-in-the-Loop Design and Evaluation of Vehicular Edge Computing Architecture with NCA&T's Autonomous Vehicle Infrastructure

2.3.1 Background Connected and Autonomous Vehicles (CAVs) are rapidly emerging as a cornerstone of next-generation Intelligent Transportation Systems (ITS), enabling safer, more efficient, and more sustainable mobility. However, large-scale CAV deployment requires communication and computing infrastructures capable of supporting ultra-low-latency data exchange, scalable data processing, and reliable coordination between vehicles and infrastructure. Traditional centralized cloud architectures alone cannot meet the stringent latency and reliability requirements of real-time vehicular applications, motivating the adoption of vehicular edge computing and distributed networking architectures. To address these challenges, a vehicular edge computing and connected vehicle networking infrastructure is needed to be developed and evaluated through field trial experiments. These trials aim to demonstrate measurable performance benefits of the proposed infrastructure using real-world data and operational conditions. The trials should also provide practical insights and recommendations regarding future infrastructure requirements necessary to support large-scale CAV deployment.

To support this effort, a scalable hardware-in-the-loop (HiL) CAV infrastructure testbed has been developed. The testbed integrates CAV, roadside access points (APs), anchor nodes (ANs) functioning as local edge servers, remote cloud computing resources, and a simulation platform that enables controlled experimentation. Local aggregation nodes interconnect APs using high-bandwidth links, enabling efficient edge computing operations and providing coordinated control over data delivery and processing. This architecture supports distributed and multi-scale computing across vehicles, edge nodes, and cloud resources. A remote cloud server supervises and coordinates operations across aggregation nodes via remote procedure call (RPC) mechanisms, ensuring system-wide orchestration and monitoring. The proposed vehicular edge computing and connected vehicle networking infrastructure supports multiple classes of data traffic generated by CAVs, roadside infrastructure, edge servers, and cloud systems. These traffic flows include safety-critical messages, sensor data streams, cooperative perception data, control commands, telemetry, and non-critical background services. Because these traffic types have widely different latency, reliability, and bandwidth requirements, uncontrolled data transmission can lead to congestion, packet loss, and unpredictable network performance, ultimately degrading safety-critical CAV applications. In field trial environments, communication links between vehicles, roadside access points, aggregation nodes, and remote cloud servers operate under limited and dynamically varying bandwidth conditions. As the number of connected vehicles and applications increases, simultaneous data transmissions may overload communication links or edge processing resources, resulting in increased delay and jitter [82]. Such performance degradation directly impacts time-sensitive applications such as collision avoidance, cooperative maneuvering, and real-time perception sharing, which require strict Quality-of-Service (QoS) guarantees [62]. Traffic shaping is a bandwidth management method that delays non-essential data packets optimizing performance for critical applications. This is therefore essential to regulate and prioritize data flows within the vehicular edge infrastructure. By controlling packet transmission rates and prioritizing latency-sensitive traffic, traffic shaping ensures that safety-critical and control-related communications receive sufficient network resources even under heavy network load. It also prevents bandwidth monopolization by high-volume applications, such as raw sensor data uploads or background synchronization services, thereby improving overall network fairness and stability.

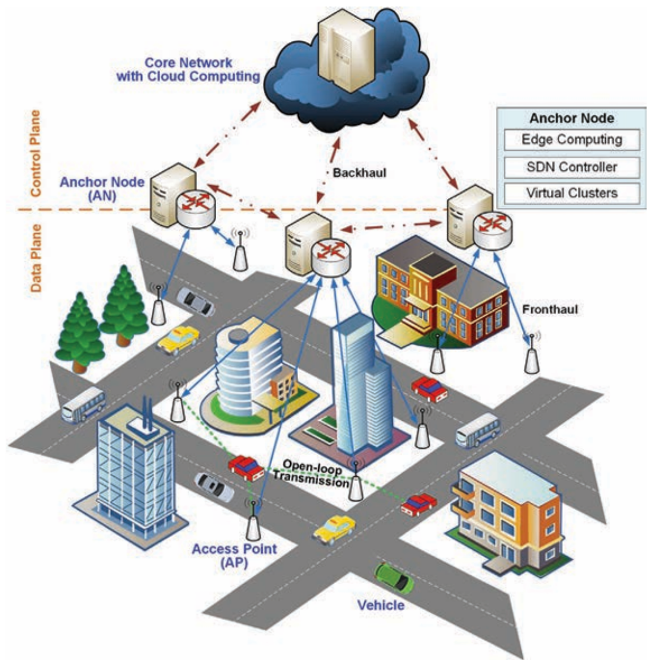


Figure 1. Architecture of Software Defined Vehicular Edge Computing.

Traffic shaping can be implemented at multiple points, including roadside access points, aggregation nodes, and edge servers, enabling coordinated flow management across vehicle-to-infrastructure and infrastructure-to-cloud links. When integrated with the software-defined vehicular edge computing control plane, traffic shaping policies can be dynamically adapted according to network conditions, application requirements, and traffic demand observed during field trials. Finally, software-defined vehicular edge computing (SDVEC) platform manage and orchestrate the underlying infrastructure components, forming a coherent control plane that integrates physical, simulated, and networked components. This combined experimental and simulation environment enables systematic evaluation of infrastructure performance, scalability, and operational readiness for future CAV deployment scenarios.

2.3.2 Proposed Method

2.3.2.1 SDVEC implementation and Hardware-in-loop simulation Our proposed system model integrates the SDVEC architecture with a HIL simulation framework to evaluate CAV services under realistic operating conditions. The model combines distributed edge computing, programmable networking, and real-time vehicular data replay to emulate large-scale CAV deployment without requiring extensive physical vehicle fleets.

The SDVEC platform forms the foundation of the system, providing distributed computing and communication services tailored for delay-sensitive vehicular applications. As depicted in Figure 1, in this architecture, roadside APs provide wireless connectivity to vehicles and are connected through fronthaul links to ANs. The ANs integrate edge computing capabilities and manage both communication and processing tasks at the vehicular edge. The SDVEC system separates networking functions into data and control planes. The data plane operates as a programmable forwarding infrastructure responsible for delivering vehicular data between vehicles, APs, and ANs using low-latency open-loop transmissions. Through coordinated transmission across multiple APs, the system supports reliable connectivity even under high vehicle mobility. The control plane resides primarily within ANs and interacts with centralized cloud resources through backhaul connections. It includes software-defined networking controllers and orchestration tools that enable real-time traffic monitoring, network management, and deployment of customized vehicular applications. Edge computing resources at ANs execute latency-sensitive services locally, reducing dependence on remote cloud servers and minimizing end-to-end delay. Sensitive vehicular data can also be filtered or processed locally to enhance privacy and security. This architecture allows scalable deployment of vehicular applications while maintaining ultra-low latency and high reliability.

To evaluate the SDVEC infrastructure under realistic operational conditions, a HIL simulation framework is

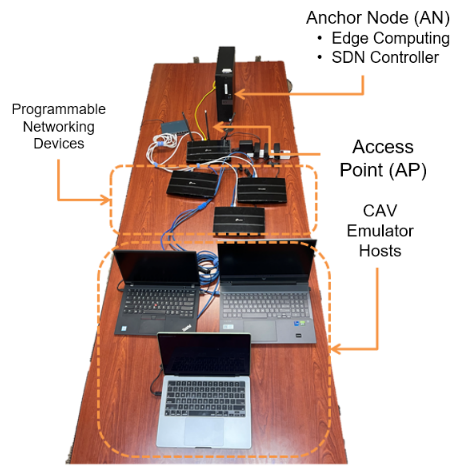


Figure 2. Implemented network testbed to realize Software Defined Vehicular Edge Computing (SDVEC) architecture.

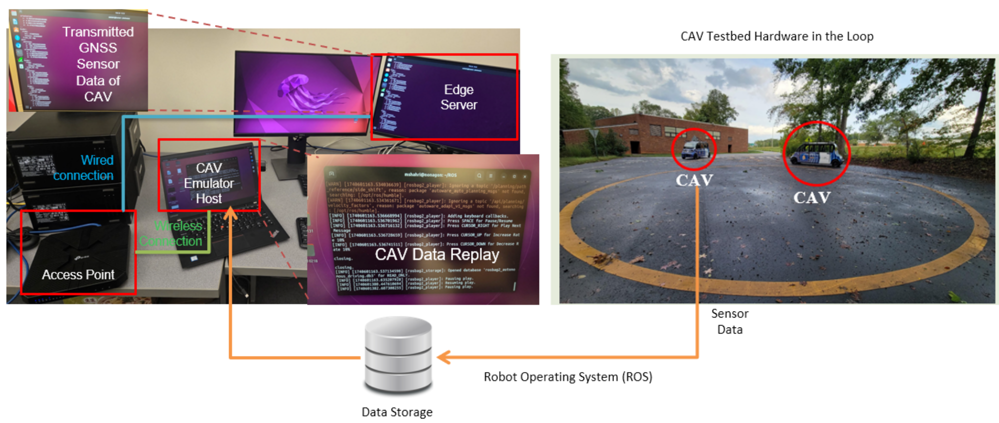


Figure 3. ROS enabled CAV-HIL simulation framework within SDVEC.

integrated into the system, as depicted in Figure 2. HIL simulation enables parts of the actual vehicular hardware or their equivalent data streams to operate within the simulation loop, allowing system validation without requiring long-term field testing. In the proposed implementation, sensor data are recorded from the CAV hardware prototype developed by NCA&T team, including perception and localization sensors. These data streams are replayed in real time from a computer connected to the SDVEC testbed as depicted in Figure 3. The replayed data emulate a live vehicle connected to the network, effectively acting as a CAV node within the system. The replay process follows real-time timing constraints to maintain correct sampling intervals and preserve the dynamics of vehicular operations. Control inputs and network responses are processed within the same timing loop, ensuring that communication delays and computation responses reflect realistic system behavior. Since control signals directly affect system stability and decision-making, maintaining real-time execution is critical for evaluating infrastructure performance. Through this approach, multiple virtual vehicles can be emulated without deploying physical vehicles, enabling scalable testing of networking, edge computing, and vehicular applications. The HIL framework therefore provides a practical and cost-effective method for validating SDVEC-based vehicular services under controlled yet realistic conditions.

In the combined system, CAV nodes generated via HIL simulation transmit vehicular data through APs to ANs within the SDVEC infrastructure. Edge nodes process these data, execute vehicular applications, and send responses or control information back through the network in real time. This closed-loop interaction allows to measure latency, reliability, and application performance under different network and traffic conditions.

2.3.2.2 Few shot learning for data-traffic classification To implement traffic shaping for regulating and prioritizing CAV data flows within the vehicular edge infrastructure, first we need to identify the CAV data traffic among heterogeneous traffic types. To address this problem, we propose an intelligent method that can quickly determine how network traffic should be identified, even when only a small amount of training data is available. Instead of requiring large datasets and long training times, our approach learns from only a few examples, making it practical for real-world deployment where collecting large amounts of labeled data is difficult and time consuming.

In simple terms, the system learns to recognize patterns in network traffic flows by comparing new traffic with a small number of known examples. When a new flow appears, the system checks which known example it most closely resembles and assigns the same priority label. This allows the network to automatically classify and manage traffic efficiently without extensive manual configuration.

2.3.2.2.1 Data Preparation The process begins by observing the first few packets of each network flow. From these packets, the system gathers basic information such as packet size, arrival timing, and communication details between sender and receiver. Using this information, it summarizes each flow using simple characteristics like how long the flow lasts, how large packets typically are, and how frequently packets arrive. These summaries allow the system to describe each flow in a compact and meaningful way without storing large amounts of packet data.

2.3.2.2.2 Example flow selection Next, the system prepares learning examples from previously observed traffic flows that already have known priority markings. For each traffic type, only a small number of representative flows are selected. These flows are then split into two groups:

- one group serves as known reference examples, and
- the other group is used to test whether the system can correctly recognize similar traffic.

This setup allows the system to learn how to distinguish different traffic types using only a few examples.

2.3.2.2.3 Flow comparison and classification The system then learns how to compare traffic flows by extracting important patterns from each flow and measuring how similar two flows are. After training, when a new and unlabeled flow appears, the system compares it with known examples and assigns it to the category that looks most similar. In result, the system answers the question of which known traffic pattern this new flow most closely resembles. The matching category is then used as the predicted priority marking. This makes it particularly suitable for dynamic vehicular and edge computing networks, where traffic patterns frequently change and rapid adaptation is necessary.

2.3.2.3 Data driven policy formulation for QoS provisioning In this part, we describe how the network can automatically adjust its resources to ensure that important data traffic receives enough bandwidth. Instead of relying on fixed settings, the system uses data collected from the network simulations to decide when adjustments are needed and then applies appropriate policies to maintain good performance.

To explain this approach, we consider a situation where data travels between an access network (such as roadside infrastructure) and an edge computing server. If simulations indicate that the available bandwidth is not enough for important traffic, the system automatically creates a policy to reserve or redistribute bandwidth. This is done by controlling how fast different types of traffic are allowed to send data and, when necessary, limiting or delaying lower-priority traffic. The system handles three main traffic situations.

- Case 1: Only One Important Traffic Flow

  In the simplest case, there is only one important traffic flow along with other less critical traffic. Here, the system ensures that the important flow receives enough bandwidth.

  If the total network demand becomes too high, the system reduces the bandwidth available to lower-priority traffic, and in extreme cases, may also slightly limit the priority flow to keep the network stable. Otherwise, it restricts only the lower-priority traffic so the important flow continues to operate smoothly.

- Case 2: Multiple Important Traffic Flows

  In more complex situations, several important traffic flows may exist at the same time. The network must then divide available bandwidth among them fairly.

  If the total demand from these priority flows exceeds available capacity, the system proportionally reduces the bandwidth allocated to each one so that all important services continue functioning without overwhelming the network. When sufficient bandwidth is available, each important flow receives the bandwidth it requires without competing with others. Lower-priority traffic is still allowed to use the network but only after priority needs are satisfied.

- Case 3: No Important Traffic

Sometimes, no traffic requires special priority treatment. In this case, the network simply returns to normal operation, treating all traffic equally without reserving bandwidth for any specific flow.

This adaptive policy approach allows the network to automatically respond to changing traffic conditions. Important vehicular and infrastructure communications continue to function reliably even during congestion, while unused capacity remains available for other applications when priority traffic is absent. Such dynamic management is essential for large-scale connected vehicle and edge computing systems, where traffic patterns constantly change and manual configuration is impractical.

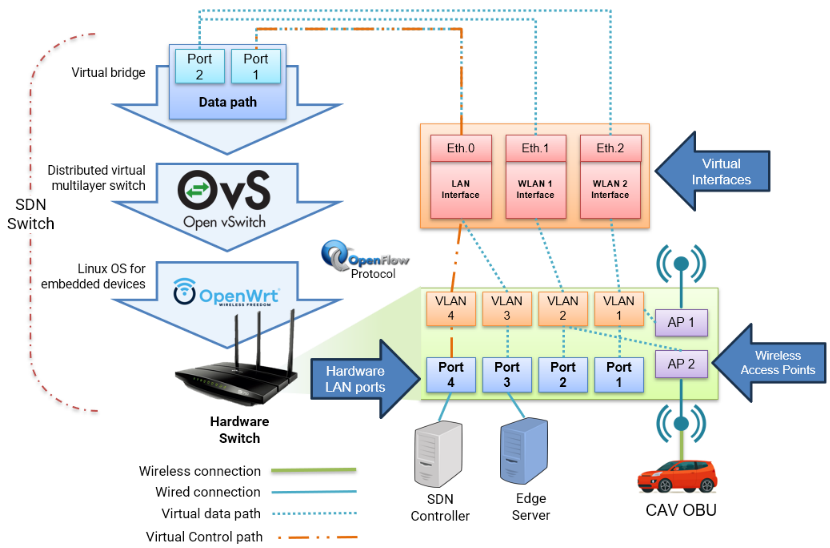
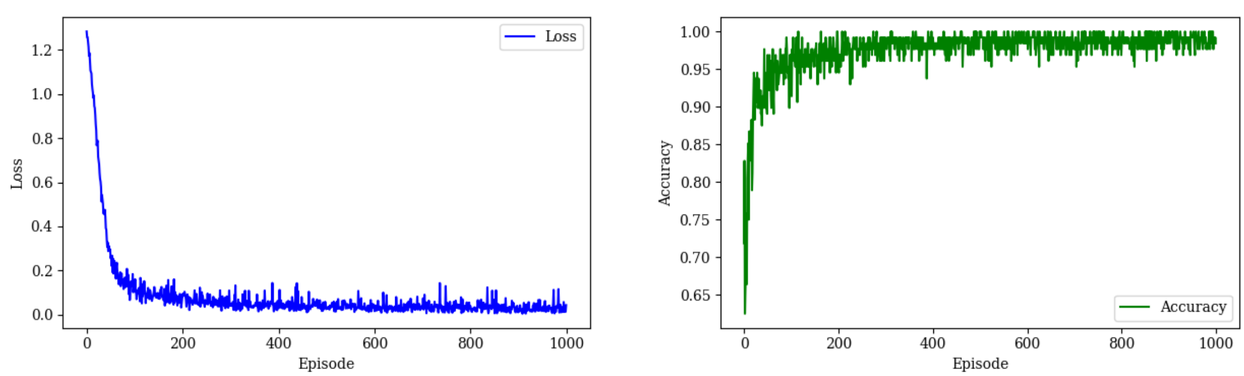


Figure 4. Implementation of programmable networking devices for HIL simulation testbed.

2.3.3 Simulation details and evaluation metrics To evaluate how well the proposed system works, we built a testing environment that combines both real networking hardware and virtual network simulations. This approach allows us to observe how the system behaves under realistic conditions while still being able to safely test different network situations in a controlled environment. As depicted in Figure 4, our setup uses common networking devices, such as commercial routers, are combined with open-source networking software that enables centralized control and monitoring of network traffic. These tools allow the system to collect traffic information and keep both the real network and its digital twin simulation synchronized. At the same time, a virtual network environment is created using network emulation software. This virtual environment makes it possible to simulate network traffic, congestion, and resource allocation decisions without affecting real users. The real router is connected to the control system so that changes tested in the simulation can automatically be applied to the physical network.

This setup forms a feedback loop between simulation and the real network. For example, if the digital twin



(a) (b)

Figure 5. Performance metrics (a) loss and (b) accuracy indicates the model's performance improvement during training.

Table 2. Experimental results for different sizes of the support set and different numbers of data packets.

Packets	Support set size = 4				Support set size = 8				Support set size = 16			
	Acc.%	Rec.%	Prec.%	F1%	Acc.%	Rec.%	Prec.%	F1%	Acc.%	Rec.%	Prec.%	F1%
5	97.88	97.89	97.88	97.88	98.12	98.15	98.13	98.13	98.56	98.58	98.56	98.56
10	97.06	97.05	97.06	97.05	98.19	98.19	98.19	98.19	98.69	98.70	98.69	98.69
15	98.25	98.29	98.25	98.26	98.12	98.12	98.13	98.12	98.50	98.51	98.50	98.50

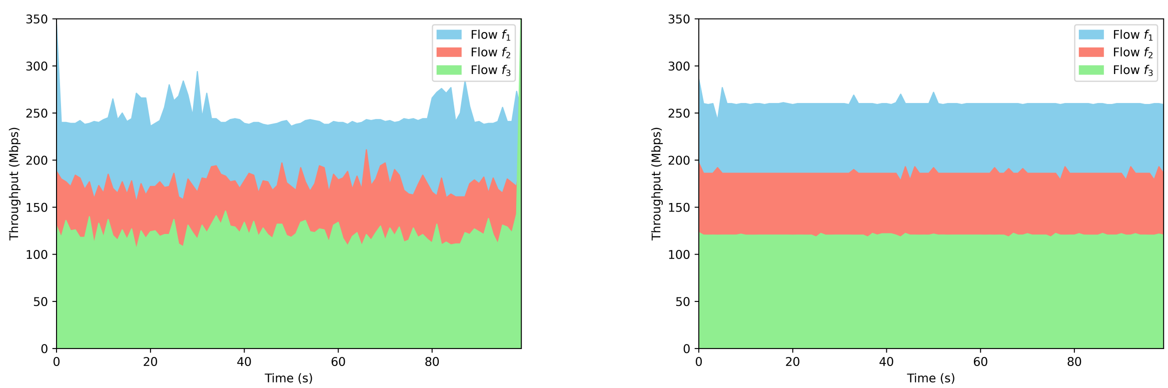
predicts that congestion or bandwidth shortage will occur, the control system can automatically update network settings on the real router to reduce congestion or prioritize important traffic. In this way, the real network continuously adapts based on predicted conditions. To train and evaluate our traffic classification method, we generated more than 8,000 simulated network traffic flows representing different network conditions and traffic priority levels. Information from packets passing through the router was collected to create training and testing datasets. Since real-world systems must often make decisions quickly, even when only a small number of packets are available, we tested how well the model performs when using different numbers of packets for prediction. The system was trained and evaluated under several configurations to observe how performance changes with varying data availability.

To measure how accurately the system classifies traffic, four common evaluation metrics were used:

- **Accuracy**, which measures overall prediction correctness,
- **Precision**, which indicates how often predicted traffic classes are correct,
- **Recall**, which measures how well the system identifies all flows belonging to each class, and
- **F1-score**, which provides a balanced measure of prediction performance.

Together, these tests show how effectively the proposed system can predict traffic priority and support intelligent network management in realistic deployment scenarios.

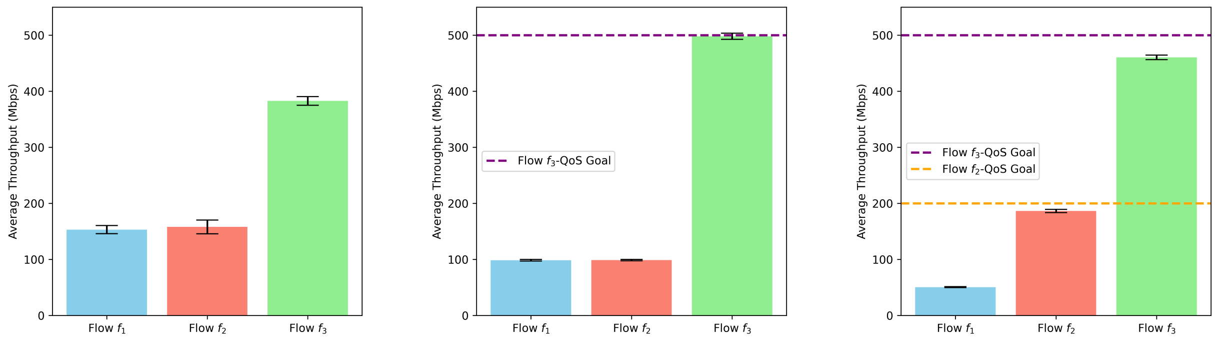
2.3.4 Result analysis and discussions The experimental results show how the proposed system improves as it learns and how it helps maintain stable network performance under different traffic conditions. During training, the model gradually becomes better at making correct predictions. Figure 5a shows that the training error steadily decreases as the system continues learning, while Figure 5b shows that prediction accuracy increases significantly after sufficient training. Testing results indicated in Table 2 shows that the prediction part of the system performs well even when it observes only a small number of packets from each traffic flow. Although performance improves slightly when more packets are available, the model already achieves strong results with very limited data. This is important because real networks often need to make decisions quickly without waiting for large amounts of information.



(a) (b)

Figure 6. The throughput of (a) unshaped traffic and (b) shaped traffic illustrates the impact of meters in HiL simulation.

Additional experiments compare network performance before and after traffic shaping is applied. Figure 6a shows that without traffic shaping, network throughput fluctuates heavily over time, meaning traffic speeds vary unpredictably. When traffic shaping is enabled, as seen in Figure 6b throughput becomes much more stable, allowing important traffic to maintain reliable performance. Further experiments examine how bandwidth is shared when multiple traffic flows compete for limited network capacity. In these tests, three flows generate different amounts of traffic, and the total demand can exceed available link capacity. When no bandwidth management policy is applied, all flows compete freely, leading to unstable performance and reduced average throughput, as seen in Figure 7a. Traffic speeds fluctuate widely because flows interfere with each other. When the proposed system is activated and only one flow is considered important, the network automatically limits less important traffic. As a result, the priority flow maintains its desired performance, and traffic variations are reduced, as depicted in Figure 7b. In another scenario, two flows are treated as important. The system then dynamically divides bandwidth between them while still allowing lower-priority traffic to continue operating at a minimum acceptable level. As depicted in Figure 7c, this prevents severe performance degradation while ensuring that all flows can still transmit data.



(a) (b) (c)

Figure 7. Average throughput from different experiments of HiL simulation shows the feedback control of network orchestration module based on QoS provisioning scheme (a) none of the network traffic flows are high priority, (b) only network traffic flow f_3 is high priority, (c) both network traffic flows f_1 and f_2 are high priority.

2.3.5 Conclusions Our proposed novel approach identifies the priority of network traffic to enable dynamic QoS provisioning within an SDN framework designed for vehicular networks. This approach leverages few-shot learning to predict priority values for previously unseen flows, which are monitored and orchestrated using the SDN-OpenFlow protocol. It further employs meter-bands in the data plane for precise control and shaping of data flows, ensuring throughput that adheres to QoS requirements. Experimental results demonstrate the effectiveness of the proposed design in priority value prediction, bandwidth management, multi-tenant resource sharing, and QoS policy enforcement, providing a scalable and efficient solution for traffic prioritization in SDN-based multi-tenant networks.

2.3.6 Future needs While the findings of this task validate feasibility of software defined vehicular edge computing and resilience in dynamic network traffic demands, continued investigation is needed in following several areas to enhance long-term deployment readiness:

- Stronger ultra-low-latency networking: The infrastructure must consistently support millisecond-level communication for safety-critical functions like collision avoidance, cooperative maneuvering, and perception sharing. This means improving end-to-end latency not just in ideal conditions, but under real traffic load and wireless variability.
- Mobility-aware handoff and session continuity: Vehicles moving across coverage zones need seamless transitions between roadside APs and edge servers. Future systems should minimize disruption during handoff so latency-sensitive applications continue without spikes in delay or jitter.
- More realistic and larger-scale field trials: The HiL testbed is a strong foundation, but broader trials are needed with more vehicles, denser traffic, mixed environments, and different environment and interference conditions.
- Application-aware networking policies: Different CAV applications have different deadlines, reliability targets, and bandwidth profiles. Future work should implement policies tailored to application intent, so the network adapts to the needs of cooperative perception differently than it does to telemetry or background syncing.

2.3.7 Relevance to NCDOT Hardware-in-the-loop (HiL) simulation allows transportation agencies to evaluate connected and autonomous vehicle systems in a safe and controlled environment before they are deployed

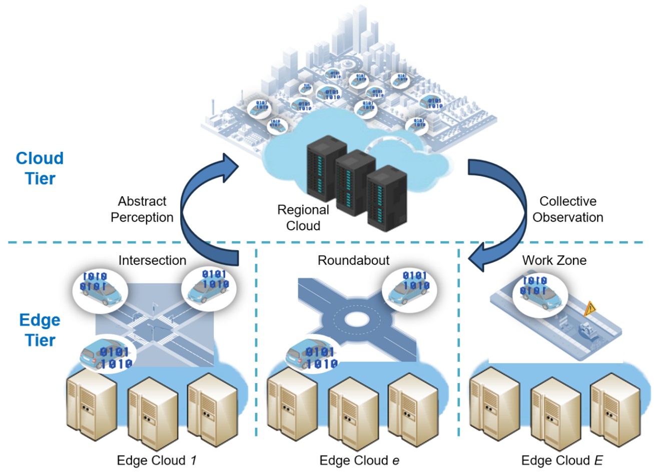


Figure 8. Proposed two-tier architecture for DT of CAVs.

on public roads. By combining real hardware, vehicle control software, sensor inputs, traffic simulation, and even mixed real-and-virtual test settings, HiL and related in-the-loop methods make it possible to study NCDOT-relevant situations such as signalized intersections, corridor traffic, mixed autonomy, ride-hailing operations, changing traffic density, and V2X-enabled roadway behavior without exposing road users to unnecessary risk. A HiL testbed also gives NCDOT a practical way to test how a new control strategy, traffic signal timing plan, roadside communication setup, or autonomous shuttle service may behave under repeatable scenarios, helping the agency identify problems early, refine designs, and build confidence before field trials or wider deployment.

2.3.8 RESEARCH PRODUCTS

2.4 Task 3: Establish a C-V2X Digital Twin for Connected Vehicular Edge Network Infrastructure

2.4.1 Background The evolution of Intelligent Transportation Systems (ITS) has been driven by the rapid advancement of connectivity, automation, and large-scale data acquisition. ITS integrates advanced communication technologies within vehicles and transportation infrastructure to enhance safety, mobility, and operational efficiency. Through vehicle-to-everything (V2X) communications, roadside sensing, and cloud-based analytics, ITS enables applications such as traffic surveillance, congestion monitoring, and cooperative driving. However, despite the proliferation of sensing and communication capabilities, the full potential of the collected data remains unexplored. Emerging paradigms such as the Internet of vehicles (IoV), Cyber-Physical Systems (CPS), and Digital Twin (DT) technologies—positioned under the broader ITS ecosystem—offer a pathway toward deeper integration, intelligence, and optimization in connected autonomous vehicle (CAV) environments. In the context of connected vehicles, IoV enables continuous acquisition of vehicle dynamics, environmental conditions, and infrastructure states. DT extends this concept by tightly coupling physical components with computational intelligence. DT architectures integrate sensing, communication, control, and actuation in feedback loops, allowing the system to analyze physical-world inputs and generate adaptive responses. In CAVs, DT supports real-time decision-making for trajectory planning, collision avoidance, and cooperative maneuvers. A fundamental requirement of a DT is the continuous real-time synchronization between the physical asset and its virtual counterpart, achieved through frequent and timely updates of state information [63].

2.4.2 System Modeling and Problem formulation The overall architecture follows a two-tier structure composed of an edge tier and a cloud tier, as depicted in Figure 8. This separation allows the system to handle both fine-grained, time-sensitive operations and large-scale, aggregated management tasks efficiently.

The edge tier is responsible for maintaining highly detailed digital twins of vehicles in near real time. It collects raw sensor data and status information from CAVs and processes this data locally to maintain accurate digital replicas. Because many vehicular applications, such as traffic safety and collision avoidance, require extremely low latency, processing at the edge tier ensures rapid response times. Each vehicle is associated with exactly one active digital twin instance at any given time. However, if an edge server becomes overloaded, another edge site within the network may host the digital twin to maintain service continuity. This collaborative capability ensures uninterrupted operation and enhances scalability.

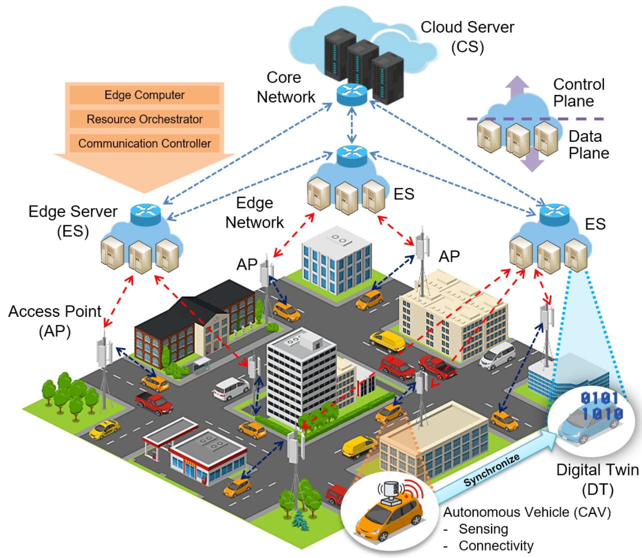


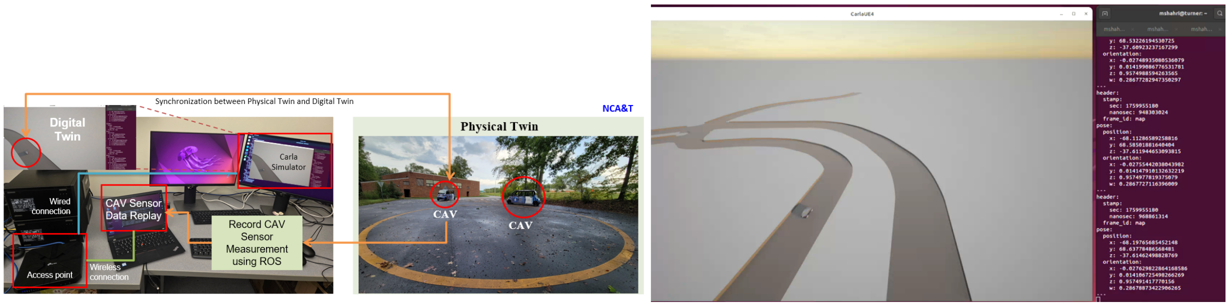
Figure 9. System model of edge network enabled DTs of CAV.

In contrast, the cloud tier maintains a broader and more abstract view of the system. Rather than storing detailed per-vehicle information, it collects summarized digital twin data and resource usage statistics from all edge servers. This aggregated information enables city-scale monitoring, long-term analytics, and global resource coordination. Applications that are less delay-sensitive, such as traffic planning and system-wide optimization, can operate at the cloud tier. The cloud tier also assists edge servers by providing global visibility into resource availability and system status, facilitating coordinated decision-making across the network.

2.4.2.1 Scalable Communication–Computation Framework To support DTs of CAVs, we design a scalable framework that tightly integrates communication and computation resources in a distributed manner. As illustrated in Figure 9, the system consists of a set of geographically distributed cloud servers, a set of edge servers deployed closer to vehicles, multiple wireless access points (APs), and a large number of CAVs generating real-time data. The cloud servers provide high-performance computing capabilities at a regional or city scale, while edge servers deliver low-latency processing close to the vehicles. Each edge server manages a local computing domain and controls several APs that provide wireless connectivity to nearby vehicles. In this structure, vehicles communicate with APs over wireless links, and APs are connected to edge servers through high-speed wired connections. Together, an edge server, its associated APs, and the vehicles served by those APs form an edge site. The edge network enables collaboration among edge sites, allowing computing tasks and digital twin instances to be distributed when necessary. This design improves scalability by ensuring that system performance does not degrade as the number of vehicles increases.

2.4.2.2 Digital Twin Synchronization Model To ensure that a digital twin accurately reflects its physical vehicle counterpart, frequent synchronization updates are required. Each vehicle periodically generates data consisting of status information (such as speed and location) and sensing information (such as camera or LiDAR data). This data must be transmitted to the designated edge server where the digital twin is maintained. The total synchronization delay consists of three components. First, there is wireless transmission delay between the vehicle and the AP. This delay depends on available bandwidth, signal quality, transmission power, and distance. Second, there is wired transmission delay between the AP and the edge server, which depends on network topology and data size. Third, once the data reaches the edge server, it must be processed to update the digital twin. The processing time depends on the computational resources available at the edge server, including CPU, GPU, and storage performance. If the total synchronization delay becomes too large, the digital twin becomes outdated and misaligned with the physical vehicle. To maintain effective operation, the system must ensure that the total update interval remains below a predefined threshold. Exceeding this threshold results in synchronization error, which can degrade the performance of time-sensitive applications.

2.4.2.3 Collaborative Computation Model Each synchronization event generates a computing task characterized by its required CPU, GPU, and storage resources. These tasks are placed into a queue at the edge



(a) (b)

Figure 10. The throughput of (a) Proposed DT implementation using CAV sensor data from NCA&T and (b) Output of digital twin of CAV in CARLA simulator.

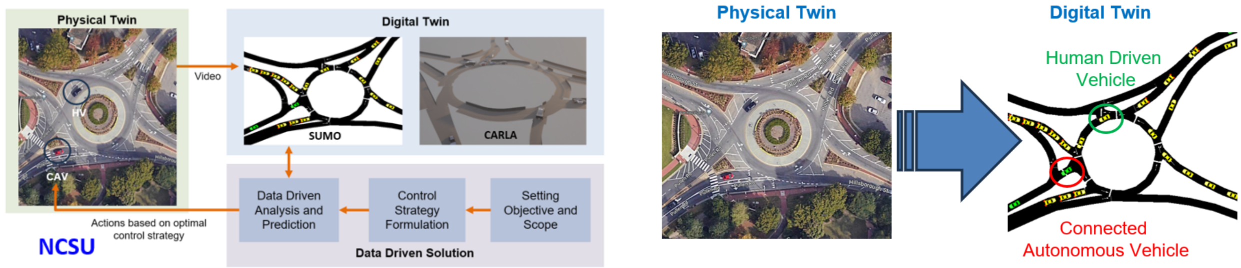
server controlling the corresponding AP. As vehicles continuously generate data, the queue may grow, and the local edge server may not always have sufficient resources to process all tasks promptly. To maintain scalability and prevent overload, the system allows collaborative computation among edge servers. If one edge server lacks sufficient computational capacity, it may offload a task to another edge server with available resources. However, resource constraints must always be respected. The total utilized CPU, GPU, and storage at an edge server cannot exceed its available capacity. Furthermore, each task must be assigned to exactly one edge server to ensure consistency and avoid duplication. To evaluate system performance, the average resource utilization across all edge servers is monitored. Efficient utilization ensures that infrastructure investments are effectively leveraged while avoiding excessive idle capacity.

2.4.2.4 Optimization Objective and Learning-Based Resource Provisioning The overarching objective of the system is to balance two competing goals: maximizing resource utilization and minimizing synchronization delay. High resource utilization ensures efficient use of infrastructure, while low synchronization delay ensures real-time accuracy of digital twins. These objectives are inherently coupled, as aggressive consolidation of tasks may increase delay, whereas conservative allocation may lead to underutilized resources. The problem is further complicated by the stochastic arrival of tasks, varying resource demands, heterogeneous hardware capabilities, and dynamic network conditions. These factors make traditional optimization techniques computationally expensive and difficult to apply in real time. To address this complexity, a learning-based resource provisioning framework is adopted. Instead of relying on fixed rules or static optimization, the system learns adaptive decision policies through interaction with the environment. This approach enables dynamic, scalable, and intelligent allocation of computing resources in distributed edge–cloud environments, ensuring reliable digital twin synchronization while maintaining efficient infrastructure utilization.

2.4.3 Proposed Method

2.4.3.1 Development of DT

Using Sensor Data We propose a DT of a CAV based on sensor data, that continuously mirrors the real vehicle's condition, behavior, and environment. This twin is constructed using real-time sensor and status data generated onboard the vehicle and transmitted to computing infrastructure for processing, as depicted in Figure 10a. In our framework, the core mechanism enabling this process is the Robot Operating System (ROS), which provides a flexible and widely adopted software environment for managing sensor data and inter-process communication in autonomous systems. Modern CAVs are equipped with multiple sensors such as cameras, LiDAR, radar, GPS, and inertial measurement units. These sensors continuously generate large volumes of data describing the vehicle's position, velocity, surrounding objects, and environmental conditions. Within the vehicle, ROS acts as a middleware that organizes and distributes this data efficiently. ROS follows a publish–subscribe communication model. In this model, different software components inside the vehicle publish data streams to specific communication channels or topics. Other components subscribe to those channels to receive the data they need. For example, a localization module may subscribe to GPS and IMU topics, while a perception module may subscribe to camera or LiDAR topics. To create a digital twin, the edge server subscribes to selected ROS topics transmitted from the vehicle. Through this mechanism, the twin receives real-time updates about the vehicle's state. As new data is published by the vehicle, it is automatically delivered to the edge server, where a virtual object is updated to reflect the vehicle's latest condition, as seen in Figure 10b. In this way, the digital twin mirrors the physical vehicle with minimal delay. A critical requirement of such DT system is synchronization. The twin must reflect the current state of the vehicle as accurately and promptly



(a) (b)

Figure 11. The throughput of (a) Proposed DT implementation using computer vision and drone data from NCSU and (b) Outcome of roundabout-digital twin in SUMO simulator.

as possible. If updates arrive too slowly, the virtual representation becomes outdated, reducing its usefulness for monitoring, decision-making, or safety applications.

Synchronization involves three main processes: transmitting data from the vehicle to the infrastructure, processing that data at the edge server, and updating the virtual model accordingly. Because vehicles generate data continuously and often at high frequency, maintaining timely updates requires careful management of communication bandwidth and computing resources. Quality of Service (QoS) mechanisms play an important role in ensuring reliable data delivery. In ROS-based systems, QoS policies define how messages are handled under varying network conditions. For example, certain data streams may require guaranteed delivery, while others may prioritize low latency over reliability. By configuring appropriate QoS settings, the system ensures that critical data—such as control and safety information—is delivered consistently, even when network conditions fluctuate. Maintaining a high-fidelity digital twin is a computation-heavy process. As the number of connected vehicles increases, the edge infrastructure must dynamically allocate CPU, GPU, storage, and network bandwidth resources to maintain real-time synchronization. If resource allocation is inefficient, delays accumulate and the digital twin may become misaligned with its physical counterpart.

Using Computer Vision We introduce a computer vision–driven DT framework for a roundabout. As illustrated in Figure 11a, the DT receives real-time video streams of the target roundabout, captured via cameras interfaced with the platform. To identify vehicles and estimate their operational states in real time, we utilize a video-based detection and data extraction approach powered by proprietary computer vision software. As vehicles enter the camera's field of view, the software performs continuous tracking and extracts key attributes, including vehicle class, spatial position (e.g., entry approach or lane), speed, and timestamp. Through an application programming interface (API), the DT platform takes this information and instantiates a corresponding virtual entity that emulates the detected vehicle. Because the current vision system cannot distinguish between human-driven vehicles (HVs) and CAVs, we incorporate vehicle-to-infrastructure (V2I) communication to identify CAVs, as seen in 11b. Their connectivity-based data are synchronized with the DT-generated virtual entities according to spatial alignment. The resulting virtual objects are integrated into a co-simulation environment that combines vehicle and vehicular network simulations, where they are updated dynamically until the vehicles exit the monitored area. This approach enables real-time emulation of both vehicular mobility and communication network behavior within the DT environment. Performance indicators including travel time, delay, average speed, queue length, connectivity status of networking devices, and communication metrics are extracted from the simulation outputs and archived in a structured data repository. From a data-driven optimization standpoint, the collected information supports real-time evaluation and benchmarking of control algorithms, traffic management strategies, and networking protocols. It also facilitates scenario-based "what-if" analysis and predictive modeling across both transportation operations and vehicular communication domains.

2.4.3.2 Intelligent Resource Provisioning for Accurate DT Synchronization The proposed resource provisioning method is designed to intelligently decide where each DT synchronization task should be processed within the distributed edge–cloud system. At any given decision moment, the system maintains a queue that contains computing tasks generated by vehicles but not yet assigned to a computing domain. Once a task is assigned to a particular edge server, that decision remains fixed until the task is completed or the server becomes available again. The key idea behind the proposed approach is that each new assignment decision depends only on the current system condition, such as available computing resources and expected delay, rather than on the full history of past decisions. Because of this property, the problem can be naturally modeled as a sequential decision-making process. To enable intelligent and adaptive behavior under dynamic conditions, we adopt a learning-based framework in which a software agent continuously observes the system state, makes task assignment decisions, and improves its strategy over time based on feedback. In this framework, the task manager deployed at an edge server acts as a learning agent. The agent observes the current system status, selects an appropriate edge server to process a given task, and receives feedback indicating how good that decision was. Over repeated interactions, the agent gradually learns how to allocate tasks efficiently, even when traffic patterns, resource availability, and network delays change over time. This approach is particularly suitable for large-scale connected vehicle systems, where traffic intensity, computational demand, and network delays vary unpredictably over time. By leveraging learning-based decision-making, the system achieves scalable, responsive, and efficient operation across heterogeneous edge–cloud infrastructures. We discuss the different phase of the learning process in following sections:

State At each decision step, the agent gathers information that describes the current operating condition of the system. This includes the communication delay experienced by a vehicle when transmitting its data to the network, the delay between access points and edge servers, and the available computing capacity across all edge servers. In addition, the agent monitors how much CPU, GPU, and storage resources are currently being used at each edge server. Collectively, this information forms the system state. Conceptually, the state captures four main aspects: the computational requirements of the pending task, the communication delay associated with transmitting vehicle data, the total available computing capacity across edge servers, and the current utilization level of those resources. By observing this state, the agent gains a complete snapshot of both network and computing conditions before making a decision.

Action After observing the current state, the agent must decide which edge server should process the task. The action therefore consists of selecting one edge server from the available set. Only one server can be chosen for each task, ensuring that the task is processed at a single location and avoiding duplication or inconsistency. This decision directly affects synchronization delay and overall system efficiency. Choosing a lightly loaded server may reduce processing delay, while selecting a geographically closer server may reduce communication delay. The agent learns to balance these trade-offs automatically.

Reward Once a decision is made, the agent receives a reward that reflects the quality of its action. The reward is carefully designed to encourage two main objectives: efficient use of computing resources and low synchronization delay. If the selected edge server processes the task without exceeding its CPU, GPU, or storage limits, the agent receives a positive reinforcement signal. However, if the assignment causes resource overload, the agent is penalized. In addition, the reward increases when overall resource utilization is efficient and decreases when synchronization delay becomes too large relative to the allowed threshold.

Over multiple decision steps within an episode, the rewards are averaged to evaluate the overall performance of the learned policy. By maximizing this long-term reward, the agent gradually learns a task allocation strategy that balances resource efficiency and real-time responsiveness. Instead of relying on fixed rules, the system continuously learns from real-time feedback and dynamically adjusts task assignments based on current network and computing conditions.

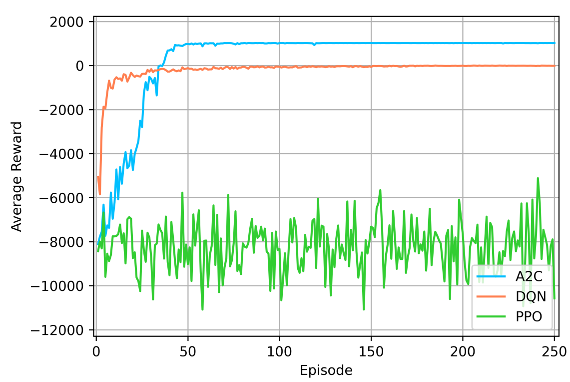


Figure 12. Episode-wise average reward during training.

2.4.4 Simulation details and evaluation metrics To examine how well the proposed resource provisioning method performs under realistic traffic conditions, we design a simulation environment in SUMO, consisting of road networks near NC State University in Raleigh. In this simulated environment, approximately 1,986 vehicles are generated per hour across multiple road segments and routes. For the purpose of evaluating the DT framework, we assume that all vehicles are autonomous vehicles. However, not all vehicles are assumed to be connected at all times. Instead, during each simulation episode, a certain percentage of vehicles is randomly selected to be connected. This percentage is referred to as the connectivity ratio (CR). The CR allows us to analyze how the system behaves as the number of connected vehicles increases. Vehicles selected as connected are associated with nearby APs based on communication range and geographical placement. Each connected vehicle generates a DT synchronization task with its own computational requirements. To process these tasks, four edge servers are randomly instantiated in each episode. These edge servers differ in computing capacity and network position, meaning that communication delay and available resources vary across servers. Each edge site contains an AP placed at a random location, serving vehicles within its communication range. To evaluate system performance, two main aspects are measured. First, synchronization delay is monitored to determine whether digital twins are updated within an acceptable time threshold. If the update delay exceeds this threshold, synchronization error occurs. Second, scheduling success is measured by determining whether a task can be assigned without exceeding the computing capacity of the selected edge server. In addition to evaluating the learning-based approach, we compare its performance with simpler decision strategies. A random strategy assigns tasks to edge servers arbitrarily, without considering system state. A greedy strategy processes tasks in arrival order and assigns each task to the first edge server in a predefined sequence that has sufficient available resources. These baseline methods provide reference points for assessing the effectiveness of the proposed learning-based approach.

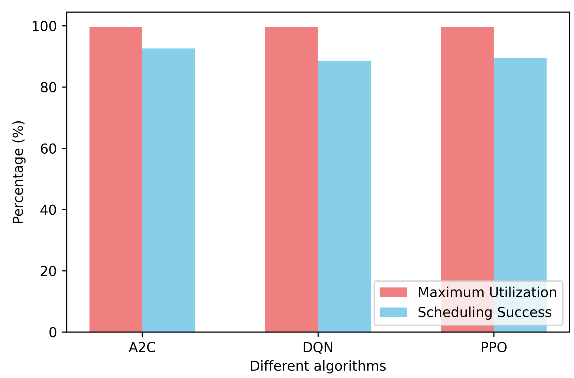


Figure 13. Comparison of two performance metrics across different scheduling algorithms.

2.4.5 Result analysis and discussions The training results demonstrate that the learning-based agent improves its decision-making ability over time. As seen in Figure 12, with training progresses across multiple episodes, the average reward increases steadily, indicating that the agent is learning to make better resource allocation decisions. Among the evaluated learning algorithms, the A2C approach achieves higher rewards compared to the alternatives, suggesting more effective learning behavior. When comparing overall system performance, several important trends emerge. As presented in Figure 13, all algorithms are capable of achieving high levels of resource utilization, meaning that the computing infrastructure is being actively used. However, utilization alone does not guarantee good synchronization performance. The key differentiator is scheduling success and synchronization delay. The greedy and random methods consistently exhibit high synchronization errors across all connectivity levels, as seen in Figure 14. Because these methods do not explicitly consider synchronization delay when making decisions, tasks may be assigned to servers that introduce excessive communication or processing delay. As the connectivity ratio increases and more vehicles generate digital twin tasks, synchronization errors grow significantly under these baseline approaches.

In contrast, the learning-based algorithms substantially reduce synchronization error. Among them, the A2C-based method achieves the lowest average synchronization error across varying connectivity ratios. Even when only 20% of vehicles are connected, synchronization error is reduced to a very small percentage. More importantly, even when 80% of vehicles generate digital twin tasks—a much more demanding scenario—the synchronization error remains relatively low compared to baseline methods.

Overall, the results demonstrate that the proposed learning-based resource provisioning strategy not only

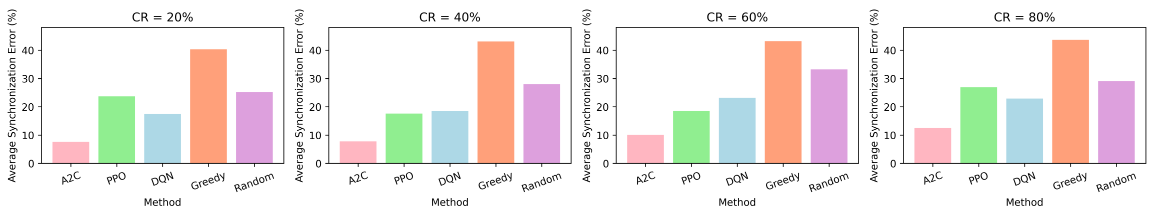


Figure 14. Comparison of synchronization error for three control strategies across varying connectivity ratios (20%–80%).

maintains high resource utilization but also significantly improves synchronization performance. This confirms the scalability and adaptability of the framework under increasing traffic load and dynamic system conditions.

2.4.6 Conclusions Despite the growing interest in DT for ITS, their uninterrupted operation under real-time, data-intensive conditions remains an open challenge. This work presents a framework that brings together DTs and MEC within a software-defined vehicular networking context. Through the development of a DRL based collaborative task provisioning algorithm, the framework effectively addresses key limitations in synchronization latency and resource allocation. Simulation results show that DRL maintains a consistently high performance across different matrices, demonstrating its effectiveness in reliable computing resource scheduling. Further evaluations based on realistic CAV traffic simulations, demonstrate that the system not only maintains DT synchronization with errors as low as 7% but also maximizes edge resource utilization.

2.4.7 Future needs The results demonstrate that a DT can be implemented using available sensor data from CAV. Future work should focus on making the DT systems faster, more reliable, scalable, and better tested in real-world conditions so it can support long-term ITS needs.

- Scalable data integration across heterogeneous sources: ITS data comes from vehicles, roadside sensors, infrastructure, environmental monitors, and cloud systems. Future work must develop architectures that can fuse these diverse data streams consistently and at scale without creating bottlenecks.
- Adaptive control and closed-loop autonomy: Since DT architectures operate in feedback loops, future work should strengthen closed-loop control where sensed conditions are analyzed in real time and translated into safe, adaptive actions for vehicles and traffic systems.
- Predictive analytics and decision intelligence: A major research opportunity is moving beyond monitoring into prediction. Future DT platforms should support forecasting of vehicle trajectories, traffic flow, hazards, and networking and communication infrastructure conditions to enable proactive rather than reactive control.
- Scalability to network-wide deployment: DT implementation for a large-scale deployment across many vehicles and road segments is much more demanding in realizing IoV enabled smart cities. Future work must address compute scaling, communication overhead, and system coordination at metropolitan or regional levels.

2.4.8 Relevance to NCDOT A digital twin offers a low-cost and flexible way to represent real transportation assets, vehicle behavior, and communication infrastructure in a virtual environment that can be continuously tested and updated. Instead of relying only on expensive and time-consuming field deployments, NCDOT can use a digital twin to evaluate different vehicle-to-infrastructure (V2I) configurations, compare signal or roadside unit settings, and predict how system performance may change across different traffic conditions, roadway corridors, and operational demands. Since the digital twin can mirror the physical system and process incoming data in a virtual space, it will enable NCDOT to examine expected performance, estimate bottlenecks, and assess the likely impact of design changes before making investments in the field.

2.4.9 RESEARCH PRODUCTS

2.5 Task 4: Enhancing Cybersecurity in the Autonomous Vehicle Ecosystem through Real-time Detection and Response

2.5.1 Background Connected and Autonomous Vehicle (CAV) technologies rely on continuous communication between vehicles, roadside infrastructure, and traffic management systems to support safety and mobility. As deployments expand across mobility corridors and traffic nodes, transportation networks increasingly depend on interconnected digital systems that operate in real time. This expanded connectivity introduces cybersecurity exposure across multiple layers of the ecosystem [108, 161]. Roadside units, wireless communication channels, backend services, as well as in-vehicle networks exchange sensitive information that must remain trustworthy and accurate. Many field devices operate in heterogeneous, multi-vendor environments and often coexist with legacy systems that are outdated, in terms of cybersecurity protections. Physical access of roadside infrastructure further increases risk.

National standards and guidance, such as the NIST Cybersecurity Framework, ISO/SAE 21434, and UNECE R155 [1, 124, 175], emphasize life-cycle risk management, secure system design, and governance practices. Although these frameworks establish foundational expectations, they provide limited prescriptive guidance for implementing scalable, real-time intrusion detection across distributed and resource-constrained CAV infrastructure. Effective cybersecurity in mobility systems therefore requires mechanisms that can identify anomalous behavior quickly, operate within resource-constrained environments, and maintain resilience in the presence of compromised components [160, 162]. Centralized monitoring approaches may introduce communication overhead, while isolated device-level monitoring limits system-wide insight.

For NCDOT, improving real-time detection and response capabilities is critical to ensuring reliable CAV operations in diverse deployment contexts. Task 4 addresses this need by evaluating scalable approaches that strengthen situational awareness and support resilient cybersecurity operations across the autonomous vehicle ecosystem.

2.5.2 Technical Approach To address the need for scalable and resilient intrusion detection across distributed CAV infrastructure, this task evaluated a federated learning-based intrusion detection framework designed for edge deployment.

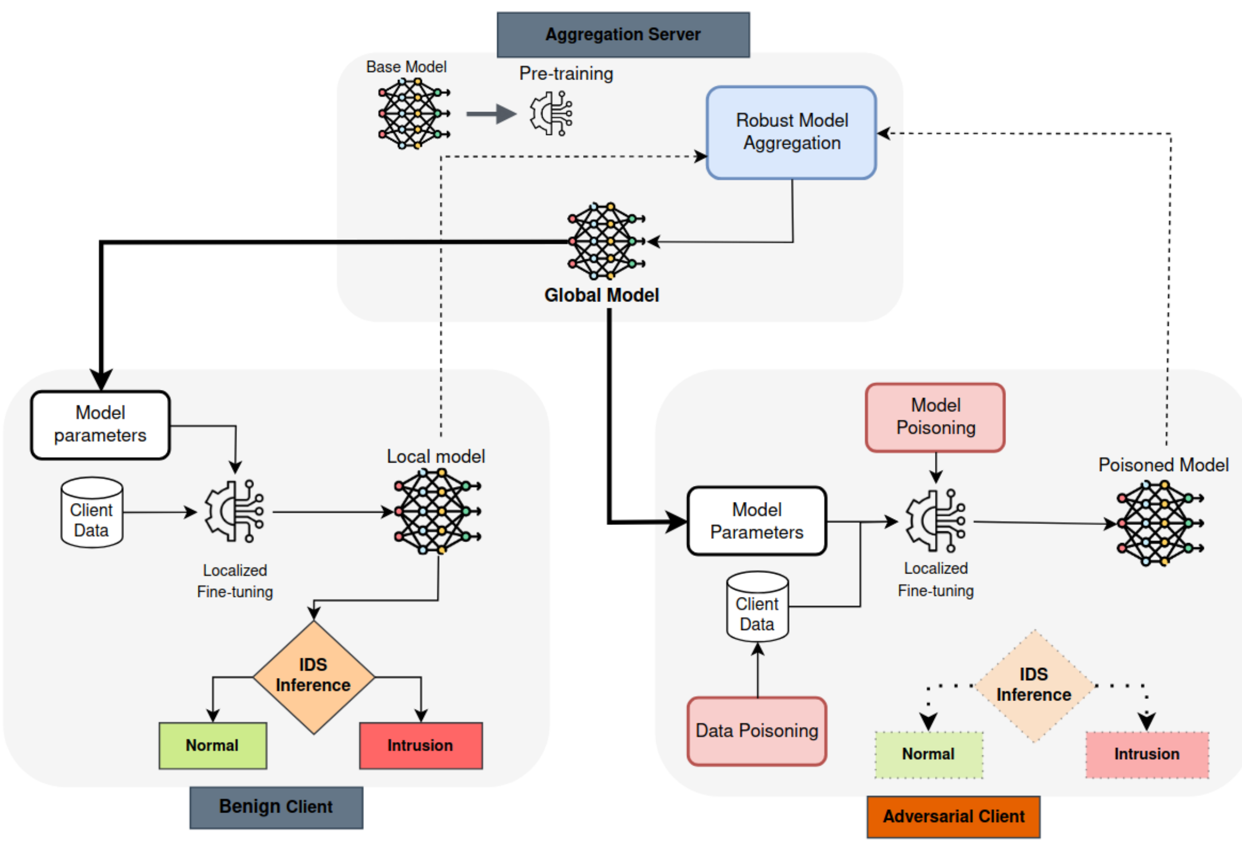


Figure 15. Overview of the FL-IDS framework depicting both benign and adversarial clients, local fine-tuning and robust model aggregation at the central server.

As illustrated in Figure 15, the architecture enables connected vehicles, roadside units, and other edge nodes, depicted as clients, to train local intrusion detection models using telemetry generated within their respective operational contexts. Rather than transmitting raw data to a centralized monitoring system, each node shares only model updates during coordinated training rounds. A central aggregation server combines these updates to produce a global detection model, which is then redistributed to participating nodes. This process supports collaborative learning while preserving local data control and reducing centralized data exposure.

Because distributed CAV environments may contain compromised or unreliable nodes, the framework incorporates robust server-side aggregation to enhance resilience. The primary aggregation strategy evaluated in this work is the coordinate-wise median, selected for its tolerance to anomalous or adversarial model updates. For comparison, conventional Federated Averaging and other robust aggregation baselines were also evaluated to assess stability under adversarial participation scenarios. This architecture enables distributed intrusion detection without centralizing sensitive telemetry, while maintaining tolerance to compromised participants and operational constraints inherent to statewide CAV deployments.

2.5.3 Results: The proposed federated intrusion detection framework was evaluated to assess (1) deployment feasibility on resource-constrained edge hardware, and (2) resilience under adversarial participation. The evaluation integrates results from both the hybrid fine-tuning architecture and the fault-tolerant aggregation analysis.

2.5.3.1 Edge Deployment Feasibility To determine suitability for distributed CAV environments, the hybrid server-edge fine-tuning strategy was evaluated on representative edge hardware. By pre-training the feature extraction layers at the server and limiting client-side updates to the classification head, the framework significantly reduced computational overhead on participating nodes.

Experimental results demonstrate:

- Up to 42% reduction in memory consumption compared to conventional federated training
- Up to 75% reduction in client-side training time under lightweight fine-tuning configurations
- Competitive detection accuracy approaching centralized baselines

Table 3. Comparison of detection performance and resource utilization across centralized, conventional FL-IDS [23], and hybrid fine-tuning configurations

Framework	Accuracy	Loss	Avg. Memory Usage, MB	Avg. Execution Time, s
Centralized	**99.8**	0.05	8.1	1339
FL-IDS [23]	97.6	0.08	8.5	1319
FedFT-3	99.2	**0.02**	6.6	1253
FedFT-1	94.3	0.15	**4.3**	**564**

Scalability analysis further showed minimal degradation in detection performance as the number of participating clients increased. These findings indicate that distributed intrusion detection can operate within realistic roadside and embedded device constraints without compromising detection quality.

2.5.3.2 Adversarial Robustness To assess resilience under realistic compromise scenarios, the framework was evaluated at adversarial participation rates of 20% and 40%, where compromised clients manipulated either training labels or transmitted corrupt model updates.

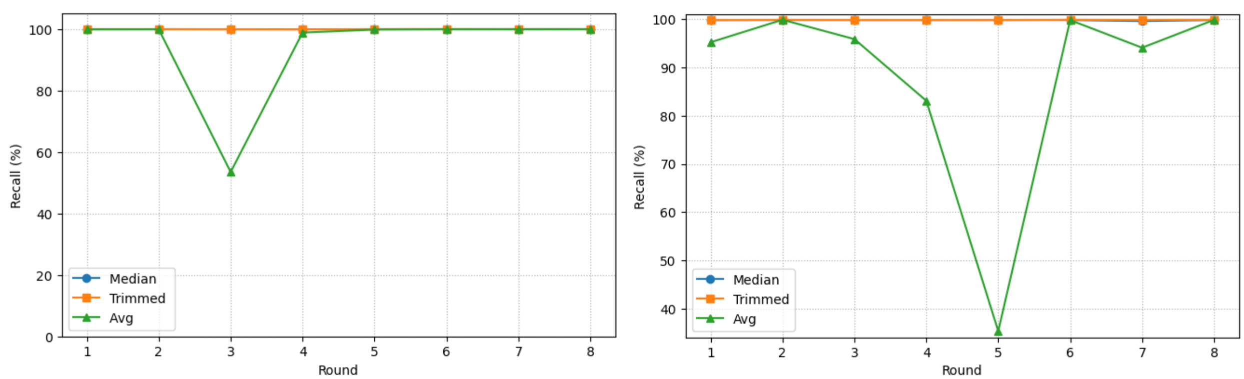
Under conventional Federated Averaging, the system exhibited substantial instability as adversarial participation increased. While mean performance metrics remained partially intact in some configurations, worst-round outcomes degraded sharply, and convergence volatility increased. This instability is operationally significant in safety-critical environments, where transient performance drops may undermine situational awareness.

In contrast, the coordinate-wise median aggregation strategy demonstrated markedly improved stability. Across adversarial rates:

- Worst-round performance degradation was significantly reduced
- Late-round variance remained low, indicating consistent convergence behavior
- Attack-class recall remained stable even under higher adversarial fractions

Table 4. Comparison of aggregation strategies under adversarial client participation, reporting average performance across late training rounds and minimum round performance at attack rates of $p = 0.2$ and $p = 0.4$.

		Final-Round Average (%)				Worst round (%)			
p (target)	Aggregator	Acc	Prec	Rec	F1	Acc	Prec	Rec	F1
0.2	FedAvg	93.25	99.96	92.15	95.93	61.82	99.98	53.43	68.80
	α-trimmed mean	99.82	$99.93^{\dagger}$	99.85	99.89	99.82	99.96	99.81	99.89
	Median	99.83	$99.93^{\dagger}$	**99.86**	**99.90**	99.82	99.95	**99.84**	99.89
0.4	FedAvg	89.99	$99.79^{\dagger}$	87.89	91.63	46.78	98.89	35.36	51.04
	α-trimmed mean	99.80	$99.91^{\dagger}$	**99.85**	**99.88**	99.56	99.64	**99.82**	99.73
	Median	99.78	99.95	99.78	99.86	99.64	99.98	99.58	**99.78**



(a) Recall at p=0.2 (b) Recall at p=0.4

- Performance volatility across rounds was substantially lower compared to averaging-based aggregation

Beyond detection metrics, coordination and deployment measurements further supported robustness. Aggregation time remained bounded relative to total round duration, and communication overhead per round remained predictable under synchronous participation. End-to-end inference latency on Raspberry Pi-class hardware remained within real-time operational thresholds.

Taken together, these results indicate that robustness is not reflected solely in average accuracy, but in stability, worst-case behavior, and operational predictability under adversarial stress. Robust aggregation materially improves tolerance to compromised edge participants in distributed CAV deployments.

2.5.4 Conclusion: Task 4 evaluated a distributed federated intrusion detection framework designed to operate within the resource constraints and adversarial realities of Connected and Autonomous Vehicle environments. The evaluation demonstrates that hybrid fine-tuning enables efficient edge deployment, reducing memory and training overhead while maintaining strong detection capability.

More importantly, the results show that robust server-side aggregation materially improves system stability under adversarial participation. While conventional averaging exhibited significant degradation in worst-round performance and convergence volatility, the coordinate-wise median maintained stable detection behavior, preserved recall under compromised participation, and reduced performance variance across training rounds.

Deployment-oriented measurements further indicate operational feasibility. Aggregation time remained modest relative to total round duration, communication overhead per round remained bounded and predictable, and inference latency on Raspberry Pi-class hardware remained within real-time monitoring thresholds. Collectively, these findings confirm that resilient, distributed intrusion detection can be implemented without centralizing sensitive telemetry and without exceeding the operational constraints typical of roadside and embedded CAV infrastructure. The framework demonstrates practical feasibility for secure, scalable deployment within statewide CAV environments.

2.5.5 Future Research Needs: While the results demonstrate feasibility and resilience, several areas require continued investigation to strengthen long-term deployment readiness.

First, future work should evaluate performance under heterogeneous and non-IID data distributions that more accurately reflect diverse roadway conditions, vehicle roles, and regional deployment differences. Real-world CAV environments are unlikely to exhibit uniform data characteristics across nodes.

Second, additional adversarial models should be examined, including adaptive and coordinated attacks that explicitly target robust aggregation rules. Expanding the threat model will provide stronger assurance of stability under evolving attack strategies.

Third, alternative federated coordination mechanisms, including asynchronous training and adaptive client selection, should be explored to reduce synchronization overhead and improve robustness in environments with intermittent connectivity or variable device availability.

Finally, expanded validation across additional in-vehicle and V2X datasets will strengthen generalizability and support cross-domain applicability within transportation infrastructure.

Continued research in these areas will enhance the reliability, scalability, and operational maturity of federated intrusion detection systems for secure Connected and Autonomous Vehicle deployments.

2.5.6 Relevance to NCDOT The findings of Task 4 directly support NCDOT's ongoing efforts to deploy secure and scalable Connected and Autonomous Vehicle infrastructure across the state. As roadside units, connected corridors, and smart work zones become more prevalent, cybersecurity monitoring must evolve beyond centralized log collection toward distributed, real-time detection capabilities.

The evaluated framework demonstrates that intrusion detection can be deployed across distributed edge assets without centralizing sensitive telemetry or overburdening field hardware. This is particularly relevant for NCDOT deployments that rely on heterogeneous equipment, multi-vendor environments, and infrastructure located in publicly accessible areas. The resilience analysis further underscores the importance of designing detection systems that tolerate compromised or misconfigured devices. In large-scale deployments, temporary faults, misconfigurations, or malicious manipulation of individual nodes cannot be ruled out. The demonstrated stability under adversarial participation supports a more fault-tolerant cybersecurity posture for statewide CAV operations.

Operational measurements, including bounded coordination cost and real-time inference performance on edge-class hardware, indicate compatibility with existing roadside and embedded infrastructure environments. This reduces barriers to incremental adoption within pilot corridors and future expansion initiatives. By integrating distributed detection mechanisms aligned with lifecycle risk management principles, NCDOT can strengthen situational awareness, reduce dependence on centralized monitoring architectures, and enhance resilience across evolving CAV deployments.

2.6 Task 5: Recommend Program Enhancements to North Carolina Readiness for Further Secure CAV Infrastructure and Applications

This section presents program enhancement recommendations for the North Carolina Department of Transportation (NCDOT) to strengthen the state's readiness for Connected and Autonomous Vehicle (CAV) infrastructure and operations. The recommendations draw from the technical findings of Tasks 2, 3, and 4 and align with NCDOT's existing programs, organizational structure, and near-term deployment activities.

2.6.1 North Carolina's Current CAV Landscape North Carolina has built a meaningful CAV foundation through several complementary programs. The NC Transportation Center of Excellence on Connected and Autonomous Vehicle Technology (NC-CAV), funded by NCDOT in 2020, brought together researchers from North Carolina A&T State University (NCA&T), North Carolina State University (NCSU), and the University of North Carolina at Charlotte (UNCC) to investigate CAV impacts, infrastructure readiness, and emerging applications. The Connected Autonomous Shuttle Supporting Innovation (CASSI) program tested automated shuttles at NC State's Centennial Campus, the Town of Cary's Bond Park, and UNC Charlotte, progressively increasing operational complexity. NCDOT's Fully Autonomous Vehicle (FAV) Committee has coordinated CAV policy discussions across state government.

In early 2025, NCDOT launched the Raleigh Multimodal Connected Vehicle (CV) Pilot, supported by a $2 million ATCMTD grant. The pilot deployed Vehicle-to-Everything (V2X) technology at 27 signalized intersections near the NCSU campus, providing real-time safety alerts through the YU2X mobile application—the state's first operational V2X deployment at scale on public roads. The U.S. Department of Transportation's deployment map records both an existing NCDOT Dedicated Short-Range Communications (DSRC) deployment and the Multimodal CV Pilot, confirming operational starting points for a repeatable corridor model.

NCDOT's Intelligent Transportation Systems (ITS) program provides the statewide operational backbone.

The agency operates Transportation Management Centers (TMCs) in Charlotte, Greensboro, and the Research Triangle; has connected hundreds of traffic signal systems to the Econolite Centracs Advanced Traffic Management System through a secure wireless subnet; improved field device uptime from approximately 48% to over 98% through a pay-for-performance ITS Resilience Project; and partnered with Flow Labs to deploy AI-powered signal operations software across more than 2,500 intersections. The 2024 Strategic Highway Safety Plan (SHSP) targets reducing fatalities and serious injuries by half by 2035, progressing toward zero by 2050. V2X-enabled safety applications offer a direct pathway to support these targets.

2.6.2 Formalize a Pilot-to-Production Corridor Framework Without a standardized process for transitioning pilots into permanent corridors, lessons learned and infrastructure investments risk remaining isolated. NCDOT should establish a repeatable corridor readiness process with clear gates progressing from planning and installation through integration testing, performance validation, and operational acceptance. Gate criteria should address interoperability verification across vendors and firmware versions, measurable performance baselines for latency and message delivery, operations and maintenance ownership, and safety outcome tracking aligned with SHSP emphasis areas.

The Task 2 hardware-in-the-loop evaluation confirmed that traffic classification and Quality-of-Service (QoS) provisioning are essential for stable communication under mixed traffic loads—capabilities that must be verified in the field, not only in laboratory settings. The Raleigh Multimodal CV Pilot provides an immediate opportunity to draft the initial readiness gates. Subsequent corridors—on I-40, near NCA&T's Greensboro test track, or other priority routes—would follow the same framework from the outset.

2.6.3 Integrate Edge Computing and Real-Time Monitoring into Corridor Deployments Current NC deployments focus on signal-level V2X communication. As applications grow more data-intensive—cooperative perception, coordinated maneuvering, real-time optimization—roadside infrastructure must process data locally. The NC-CAV research agenda specifically identified the need for low-latency edge computing and tools to detect abnormal system behaviors. For future corridors, NCDOT should include edge computing as a standard design element at priority intersections: cabinets sized for computing hardware, sufficient backhaul bandwidth consistent with the Software-Defined Vehicular Edge Computing (SDVEC) architecture from Task 2, and baseline device-health telemetry tracking CPU usage, memory, temperature, and communication status.

Task 3's Digital Twin research demonstrated that distributing computation across edge servers reduced synchronization error to as low as 7% even when 80% of vehicles generated data simultaneously. Edge computing is therefore a foundational requirement for next-generation connected infrastructure, not an optional enhancement. New deployments should integrate into NCDOT's existing Centracs, TMC, and backhaul architecture rather than operating as standalone systems, with the ITS Resilience Project's maintenance model extended to cover edge hardware.

2.6.4 Use Digital Twin Technology for Planning and Performance Evaluation A Digital Twin—a virtual replica continuously updated with real-world data—allows NCDOT to test changes, evaluate outcomes, and identify problems before committing field resources. For each new corridor, NCDOT should develop a Digital Twin mirroring roadway geometry, signal timing, traffic patterns, and communication infrastructure. Task 3 demonstrated two viable approaches: sensor-based twins using Robot Operating System (ROS) vehicle data, and computer vision–based twins using camera feeds at intersections. The SUMO-based environment modeled approximately 1,986 vehicles per hour on NCSU-area road networks, enabling realistic evaluation of resource provisioning strategies.

Digital Twin outputs—travel time, delay, queue length, speed, and communication metrics—support performance benchmarking and "what-if" analysis without disrupting active operations. The Raleigh pilot's 27 instrumented intersections are a natural candidate for the first operational Digital Twin. NCDOT can partner with NC-CAV teams to extend the project's simulation tools into a standing capability integrated with corridor data.

2.6.5 Establish Distributed Cybersecurity Monitoring Across CAV Infrastructure Each new connected device—RSUs, signal controllers, edge nodes, V2X radios—expands the attack surface. Centralized monitoring introduces overhead and single points of failure. NCDOT should integrate distributed cybersecurity monitoring from the design phase. The federated learning-based intrusion detection framework from Task 4 demonstrated feasibility on resource-constrained hardware (Raspberry Pi-class devices), achieving up to 42% memory reduction and 75% training time reduction while maintaining accuracy approaching centralized baselines. Nodes share only model updates, not raw telemetry, preserving local data control.

Robust aggregation is critical. Coordinate-wise median aggregation maintained accuracy above 99% even when 40% of nodes submitted adversarial updates, while conventional averaging exhibited substantial worst-round degradation. Because a single period of degraded detection in a safety-critical environment can have serious consequences, worst-round performance—not average accuracy—is the operationally significant metric. NCDOT should begin by requiring device-health telemetry and anomaly flagging on all new installations as the foundation for more advanced detection.

2.6.6 Institutionalize Lifecycle Cybersecurity Governance and Supply Chain Security Cybersecurity must be embedded across the entire infrastructure lifecycle, not treated as a one-time check. The NIST Cybersecurity Framework 2.0 introduces an explicit Govern function linking detection and response to organizational oversight [124]. ISO/SAE 21434 ties threat analysis and security requirements to verification and post-deployment monitoring [1]. NCDOT should formally align CAV programs with these frameworks so that cybersecurity requirements appear in project scoping documents, procurement solicitations, acceptance criteria, and maintenance contracts.

Supply chain risk requires equal attention. Many field devices operate in multi-vendor environments alongside legacy systems lacking modern protections. UNECE Regulation No. 155 requires structured cybersecurity management across vehicle supply chains [175], and NHTSA treats monitoring, incident response, and vulnerability disclosure as lifecycle activities [112]. NCDOT procurement policies should require vendors to provide evidence of secure development practices, firmware update mechanisms, documented patch cadence, and vulnerability disclosure processes. Equipment that cannot demonstrate these capabilities should undergo additional risk assessment before deployment.

2.6.7 Strengthen the ITS Program as the Operational Backbone for CAV NCDOT's ITS program already manages signal systems, traveler information, incident management, TMCs, dynamic message signs, commercial vehicle operations, and transit management—the exact operational platform CAV extends. Rather than deploying CAV as parallel standalone pilots, NCDOT should integrate RSUs, connected controllers, edge nodes, and V2X systems into this existing architecture. TMC capabilities should expand to include CAV corridor performance, edge computing health, and cybersecurity status. The ITS Resilience Project's maintenance model should apply to all CAV equipment.

Workforce development is essential. Division-level ITS and traffic engineering staff—who already maintain signal systems and field devices—are natural candidates for CAV equipment responsibilities and should receive training on V2X protocols, edge computing, and cybersecurity monitoring. Tasks 2, 3, and 4 each demonstrated that CAV performance depends on system-level coordination across communication, computing, and security components, which is precisely the function NCDOT's ITS program provides. The Centracs signal system offers an immediate integration point for RSU status and V2X metrics as deployments expand.

2.6.8 Establish a Statewide CAV Cybersecurity Test and Validation Program Vendor attestations do not substitute for structured testing. NCDOT needs independent capability to evaluate equipment under both normal and adversarial conditions before field deployment. FHWA's Transportation Cybersecurity Strategic Plan [43] and CISA's Cybersecurity Performance Goals 2.0 [33] both support measurable evaluation practices for critical infrastructure. The NCA&T test track and the SDVEC hardware-in-the-loop testbed from this project provide existing infrastructure for a validation program.

Task 4 demonstrated that benign-condition testing alone does not reveal how systems behave when nodes are compromised. Standardized evaluation criteria should include worst-case performance, convergence stability, coordination overhead, and inference latency on target hardware—applied consistently across vendors. NCDOT can partner with NCA&T and NCSU to formalize the project's testbed into a shared validation resource, beginning with the RSUs and controllers deployed in the Raleigh pilot.

2.6.9 Implementation Priorities **Near-term (within 12-24 months):** Formalize the pilot-to-production corridor framework using the Raleigh pilot. Require device-health telemetry on all new RSU and signal controller installations. Begin integrating CAV monitoring into TMC operations. Update procurement language to include cybersecurity requirements and vendor vulnerability disclosure obligations.

Medium-term (24-48 months): Include edge computing readiness in next corridor design requirements. Pilot federated intrusion detection on a subset of field devices. Develop a corridor-level Digital Twin for the Raleigh pilot. Initiate workforce development for Division ITS staff. Begin aligning CAV cybersecurity practices with NIST CSF 2.0 and ISO/SAE 21434.

Longer-term (48+ months): Establish the statewide cybersecurity test and validation program. Expand Digital Twin deployment to additional corridors. Extend the ITS Resilience maintenance model to all CAV infrastructure. Apply the corridor framework to at least two additional deployments. Implement structured supply chain security controls across all divisions.

Chapter 3 : Research Findings under Project 6: Define and implement potential usecases for deployment

3.1 Background

Connected autonomous vehicles (CAVs) promise to provide efficient solutions for increasing transportation demands [64]. 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. 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. Despite all these modular developments on AV technology, communication, and computation technologies, CAV deployments are often limited to closed test tracks, and the CAV use cases yet to emerge.

The goal of this project is to explore emerging applications of CAVs to quantity their impacts via simulation analysis and field experiments. This will be achieved through pursuing the following objectives:

- **Objective 1:** Developing A Distributed Model-Free On-Demand Ridesharing Framework,
- **Objective 2:** Quantifying the Effects of CAVs on Traffic Operations at Roundabout by Simulation Analysis and Field Experimentation,
- **Objective 3:** Developing a Robust UAV-based Traffic Monitoring System for Complex Urban Environments.

3.2 Task 1: Literature Review

Despite the great progress on the development of autonomous vehicles, actual benefits and use cases of deployment of connected AVs have yet to be explored. One interesting use case would be the impact of CAVs on traffic management at the roundabouts. There are only a few studies that focused on the trajectory control of CAVs at roundabouts. Azimi et al. (2013) proposed a protocol to prioritize the access of CAVs to the conflicting areas of a roundabout based on a predefined assigned priority or a first-come-first-serve (FCFS) basis. The protocol was designed for a traffic stream of 100% CAVs based on dividing the circular roadway of a roundabout into several cells such that each cell could be occupied by only one vehicle at a time. Martin-Gasulla and Elefteriadou (2019) used the FCFS principle and developed a trajectory control logic for a traffic stream of only CAVs. The logic was a combination of speed adjustments for CAVs at the entry approaches and a conventional car-following model for the CAVs on the circular roadway of a roundabout. Bakibillah et al. (2019) developed a multi-level cloud-based controller to cluster vehicles, determine the merging sequence, and optimize trajectories of CAVs at a roundabout. Zhao et al. (2018) developed a CAV trajectory controller to minimize the acceleration changes subjected to the maximum and minimum speed and acceleration, and equations of motions to consider vehicle dynamics. They also used an FCFS principle for a roundabout with two entry approaches where vehicles needed to maintain rear-end safety distances. They also applied the control logic to a semi-automated environment by assuming that CAVs were controlled with the FCFS logic as long as safety constraints were not violated. When safety requirements could not be ensured with the FCFS logic, a car-following model was used instead. However, this approach assumed that only one vehicle can be present in the merging areas of a roundabout to eliminate lateral collisions. Mohebifard and Hajbabaie (2021 and 2022) developed methods to optimize the trajectory of CAVs in single roundabouts with different CAV market shares in the traffic stream. They implemented their control strategy in a microscopic traffic simulator (PTV Vissim) and made extensive runs with different traffic demand levels and CAV market shares. Their findings indicate that increasing

CAV market share, reduces travel time and delay, increases safety, improves rider comfort in both CAVs and human driven vehicles, and consequently could reduce fuel consumption. There is a need to expand on these experiments with considering different demand levels, demand patterns (symmetric/asymmetric, different turning percentages), geometric conditions, and heavy vehicle presence in a computer-based simulated innironemnt to understand the effects of CAVs better. Furthermore, real-world tests in roundabouts are needed to better understand the effects and be able to interpret the findings of the simulation studies more accurately.

An interesting use case of CAVs is to use them for ridesharing. The increase in personal mobility has contributed immensely to serious transportation issues like traffic congestion and environmental pollution. To address these issues, researchers have considered on-demand ridesharing for CAVs as a possible solution. In Alonso-Mora et al (2017), the authors demonstrated that 20% of the current taxi fleet of New York city is sufficient to satisfy 98% of the demand when considering ridesharing. This significant reduction in the fleet size will contribute to reducing traffic congestion. The authors in C Li et al (2021a) improved on the computational efficiency of Alonso-Mora et al (2017). In C Li et al (2021b), the benefits of ridesharing in terms of profit generated to the service provider is investigated. These studies show that the adoption of ridesharing for CAVs can significantly enhance the transportation system.

Another important challenge is the control of automated vehicles in a mixed traffic setting when both automated vehicles and human-driven vehicles are driving. In [14, 15], human-like control of automated vehicles is investigated. The work in [9, 66, 135] investigates the the driver intention estimation which can be used for control of automated vehicles when interacting with human-driven vehicles in a mixed-traffic setting. To investigate these challenges and implement the proposed use cases, we will utilize a connected and automated vehicle (CAV) testbed developed by our research team with support from theNCDOT [70, 128].

Despite all these progresses, there are still many challenges that need to be addressed, such as development of more sophisticated algorithms and techniques for data processing and analysis, regulatory and safety concerns, integration with other intelligent transportation systems, and smart city applications. Further research in these areas is needed to fully realize the potential of UAVs for traffic monitoring.

3.3 Task 2: Developing A Distributed Model-Free On-Demand Ridesharing Framework

3.3.1 Background Ridesharing presents a viable solution for mitigating urban mobility challenges, including traffic congestion, environmental pollution, and parking space shortages, which are predominantly driven by the rise in personal vehicle usage [4, 144]. By offering shared transportation options, ridesharing services reduce the overall number of vehicles on the road, leading to lower greenhouse gas emissions, decreased energy consumption, and more efficient use of urban infrastructure. The rapid advancement of smart mobile devices and scalable data processing technologies has further enhanced the capabilities of ridesharing fleet operators, such as Uber, Lyft, and Didi, enabling them to track vehicles' GPS locations and respond to passenger pickup requests in real time. By employing predictive algorithms, ridesharing platforms can anticipate future passenger[1] demand and identify emerging mobility patterns within the urban environment. Through the analysis of historical and real-time data, such systems can forecast demand hotspots and dispatch vehicles proactively to areas where passenger requests are expected to arise, thereby optimizing fleet distribution and minimizing idle time. This predictive approach not only enhances the utilization of available vehicles but also significantly reduces passenger waiting times by ensuring that vehicles are strategically positioned in advance of demand surges [102].

The proactive dispatch of vehicles across urban areas and the efficient operation of ridesharing services present the following technical challenges (TCs):

1. Accurately forecasting future passenger demand across various city regions by capturing the latent dynamics and inherent uncertainties of the urban road network.

2. Developing equitable and accurate pricing strategies, including incentive mechanisms, to effectively balance passenger fares[2] and driver motivation for providing transportation services.

3. Ensuring real-time, reliable computation of optimal vehicle routing, minimizing travel distances while considering dynamic traffic conditions.

To address these challenges, this project proposes an integrated framework for demand prediction, pricing, and routing to enhance ridesharing services.

[1]Passengers and customers are used interchangeably.
[2]Price and fare are used interchangeably.

3.3.2 Literature Review Existing ridesharing approaches can be categorized into centralized, decentralized, and distributed approaches [203]. Hence, the review is based on these categories. A centralized approach, which is based on the concept of shareability networks, is introduced in [142] to model the potential benefits of vehicle pooling. Their framework efficiently computes optimal sharing strategies by translating spatiotemporal sharing problems into a graph-theoretic method. However, their method is restricted to low-capacity vehicles and static routes. To address the limitations in [142], an on-demand high-capacity ridesharing centralized approach is introduced in [7]. The authors proposed an anytime optimal algorithm capable of dynamically assigning multiple passengers to vehicles in real-time, ensuring optimal routing while minimizing waiting times, travel delays, and operational costs. Nevertheless, their method suffers from a high computational cost. The computational efficiency of the method in [7] is enhanced by considering a federated optimization architecture that distributes computation across multiple resources in [152]. Additionally, the performance of the approach in [7] is improved in [80, 81] by employing optimal schedule pool algorithm for dispatching vehicles. [84] addressed the challenges of balancing supply and demand in ride-sourcing services under real-time conditions and stochastic traffic in large-scale urban road networks. They propose a robust and scalable framework that combines reinforcement learning with centralized programming (CP) to optimize both order matching and vehicle relocation decisions within a Markov Decision Process (MDP) framework. Furthermore, numerous works have employed centralized approaches to optimize the ridesharing profit [76, 205, 206, 213], rebalancing vehicles from low or no demand to high demand regions [8, 125, 153, 170, 187], fleet management [22, 110, 172], and vehicle dispatch [94, 95, 156].

In [28], a decentralized ridesharing and vehicle-pooling mechanisms that ensure fair cost-sharing among commuters is explored. The study introduces several fair cost-sharing mechanisms, including equal, egalitarian, proportional, and segment-based methods, and examines their impact on stable matching outcomes. The authors in [79] formulate the ride-sharing problem as a multi-agent decentralized reinforcement learning task and utilize a graph attention network to model vehicle-request interactions through a request-vehicle (RV) graph. This graph-based approach enables the efficient encoding of the shareability of requests and coordination among vehicles. The framework also integrates rebalancing strategies for better fleet management. To address the computational challenges posed by the dynamic and stochastic nature of the ridesharing problem, the authors in [197] applied a spatial-temporal decomposition heuristic and solved the subproblems using Approximate Dynamic Programming (ADP). In [145], a neural network-based ADP framework is proposed to address the limitations of existing myopic approaches by modeling the ridesharing matching problem as an ADP problem and incorporating a deep neural network to estimate value functions, which allows for the handling of complex combinatorial assignments of multiple passengers to vehicles.

In recent times, advanced reinforcement learning algorithms have proven to be effective in addressing the ridesharing problem [132]. [120] introduces a model-free, reinforcement learning-based approach (MOVI) to fleet management, focusing on proactive dispatching of vehicles to predicted future pickup locations. Conventional model-based methods rely on predefined system models, which may not be flexible enough for highly dynamic environments like fleet management. MOVI instead uses a distributed Deep Q-Network (DQN) framework, where individual vehicles independently learn their optimal dispatch policies without system-wide coordination. The paper demonstrates that this approach can significantly reduce the number of unserviced requests and passenger waiting times compared to both no dispatching and a centralized model-based receding horizon control (RHC) approach. However, MOVI is restricted to only dispatching the vehicles without considering ridesharing. Similar studies can be found in [158, 185, 190]. An extension of [120] can be found in [5], where the authors considered both ridesharing and vehicle dispatch. Similarly, the authors in [198] proposed using a Graph Neural Network (GNN) to represent road networks, which preserves the structure of the network and captures the geographical density and directional traffic flows. This graph-based approach enhances the learning process by incorporating GNN layers within a Deep Q-Network (DQN) framework, improving vehicle relocation policies. Lastly, a distributed joint framework that optimizes ride-sharing services by addressing vehicle-passenger matching, pricing, and dispatching decisions is proposed in [57].

3.3.3 Proposed Method: Figure 16 represents the overall system architecture of the proposed approach. The proposed framework can be summarized into four main components: (1) service area, (2) central unit, (3) Deep Q-Network (DQN) engine, and (4) pricing model. Additionally, the central unit comprises our proposed integrated routing engine (IRE) and demand prediction model, a matching agent, and an estimated time of arrival (ETA) model. Specifically, the central unit performs the following roles: (1) maintaining and updating the environment states i.e., geographical locations of vehicles and requests, number of occupied vehicles, number of idle vehicles etc, (2)

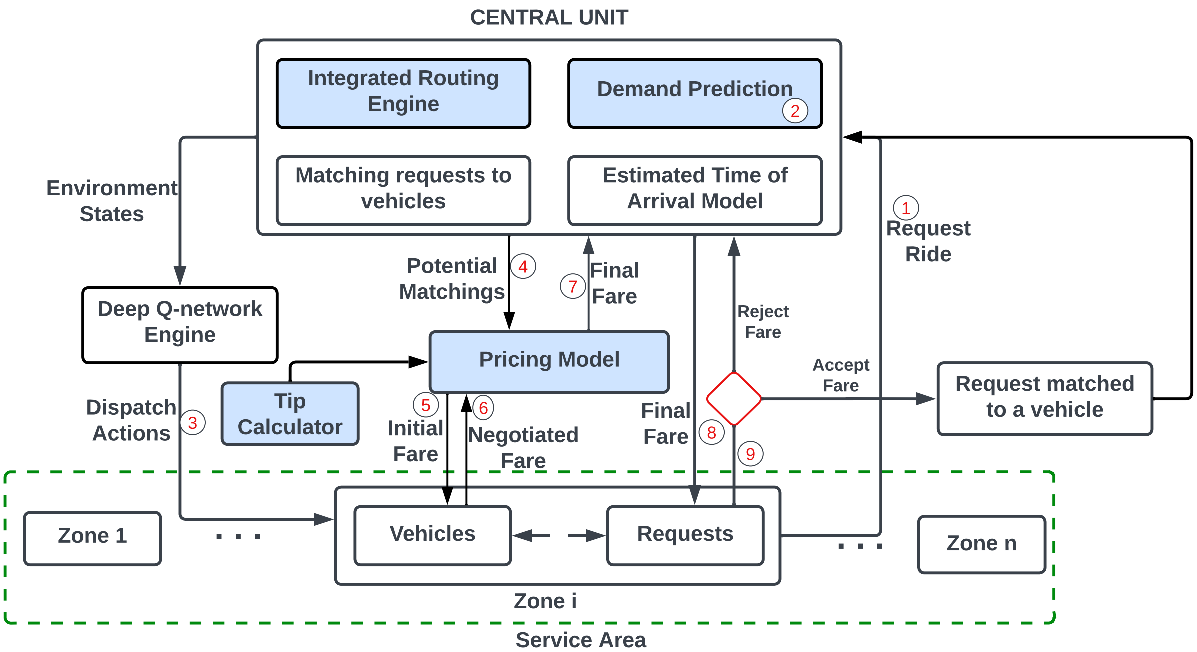


Figure 16. Overall architecture of the proposed distributed ridesharing framework. The circled numbers represent the sequence of operations.

potentially matching vehicles to requests based on their proximity, (3) an IRE responsible for computing the shortest route for vehicles, (4) a demand prediction model for estimating the future demand in all zones, and (5) utilizes an ETA model for computing and perpetually updating the estimated arrival time. We first divide the service area into N_z number of zones. Each zone z contains a number of vehicles V and requests R. For every time step, a request is made for a ride using for example, a mobile app (step 1). In step 2, the demand prediction model predicts the future demand. Then, considering the current and predicted demand in each zone z, vehicles employ a DQN engine to determine the best dispatch decision to take with regards to being dispatched to a high demand zone (step 3). Once the vehicle arrives in zone z, the central unit's matching agent greedily assigns requests to the vehicle based on their proximity (step 4) and recommends an initial fare to the vehicle (step 5). The vehicle either accepts the initial fare or proposes a new fare by considering the expected discounted reward learnt from the DQN, and whether the request's location is in a potential hotspot zone. Based on its own utility function, the request decides to accept or reject the fare. Finally, regardless of the matching outcome, the information is made available to the central unit to update the system by either re-assigning the request to another vehicle if it's unmatched or removing the request if it's matched. The IRE is subsequently utilized by the vehicle to compute the shortest route for both picking up the passenger and dropping them off at their final destination.

3.3.4 Simulation Details In our experiment, we utilized the Manhattan map sourced from OpenStreetMap (OSM) [55], in conjunction with a comprehensive, realistic open-source dataset of taxi trips in New York City [164]. For each trip, we extract key details including request time, pick-up time, passenger count, and pick-up and drop-off locations. This detailed trip information serves as the foundation for constructing our demand prediction model. The simulation initializes 8,000 vehicles, which are randomly distributed across the city at the start of the simulation. It is important to note that the vehicles are not deployed all at once; instead, they are gradually introduced into the market at each time step throughout the simulation.

We adopted the default training and hyperparameter settings as outlined in the simulator of [120] for the DQN. Specifically, the discount factor, λ, is set to 0.98, and the optimizer used is RMSprop. The batch size is 128, with a learning rate of 0.00025. For RMSprop, the momentum is 0.95, and epsilon is 0.01. The ε value, relevant to the ε-greedy method, decays linearly from 1.0 to 0.01 over the first 3,000 steps.

3.3.5 Evaluation Metrics We considered the following evaluation metrics for assessing the performance of our framework:

- Average profit: this metric denotes the net profit earned by each vehicle per hour of service.
- Average travel distance: this metric represents the distance traveled by each vehicle per hour of service.
- Average idle time: this metric represents the duration during which a vehicle is neither occupied by passengers nor generating profit, yet continues to incur fuel costs. It is the difference between the working time, and when the vehicle is occupied or assigned.
- Average wait time: this metric measures the time that customers wait until they are picked up by a vehicle.
- Utilization rate: this metric represents the ratio of the number of vehicles that are occupied relative to the total number of vehicles on duty.
- Rejection rate: this metric indicates the proportion of rejected requests relative to the total number of requests.

3.3.6 Algorithm Comparison To highlight the efficacy of our proposed framework, which integrates a demand prediction model, pricing, and routing strategy, we conducted a comprehensive comparison against established baseline methods. Note that the demand prediction model, pricing, and routing strategy form part of the overall proposed framework in Fig. 16. This analysis underscores the advantages and significance of our approach.

3.3.6.1 Demand prediction models

- No convolution operation (DQN-!C): this method does not utilize any demand prediction model to predict the demand in the zones.
- Standard convolution operation (DQN-SC) [5, 120]: in this method, a conventional convolution operation is employed for predicting the demand.
- Diffusion convolution operation (**DQN-DC**) (ours): this is our method which employs a diffusion convolution operation for predicting the demand.

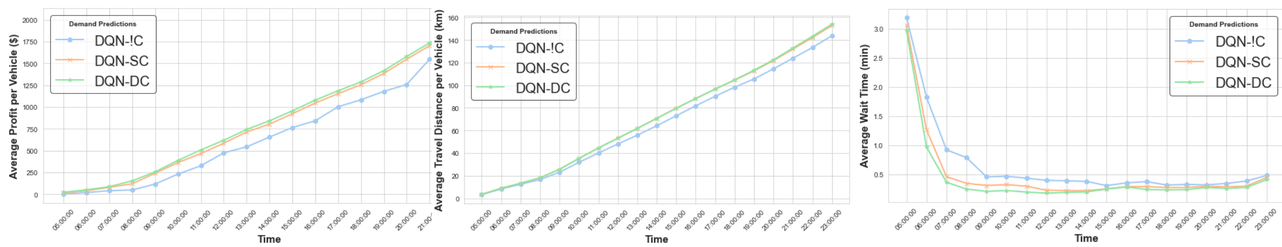
3.3.6.2 Pricing strategies

- No pricing strategy (DQN-!P) [120]: in this setting, no pricing strategy is implemented.
- Pricing strategy (DQN-P) [56]: this method implements a pricing strategy without considering tipping of the vehicles.
- Pricing strategy with standard tip (**DQN-PST**) (ours): this is our method which implements a pricing strategy that considers standard tipping of vehicles.
- Pricing strategy with adaptive tip (**DQN-PAT**) (ours): this method is similar to DQN-PST except it implements an adaptive tipping strategy.

3.3.6.3 Routing strategies

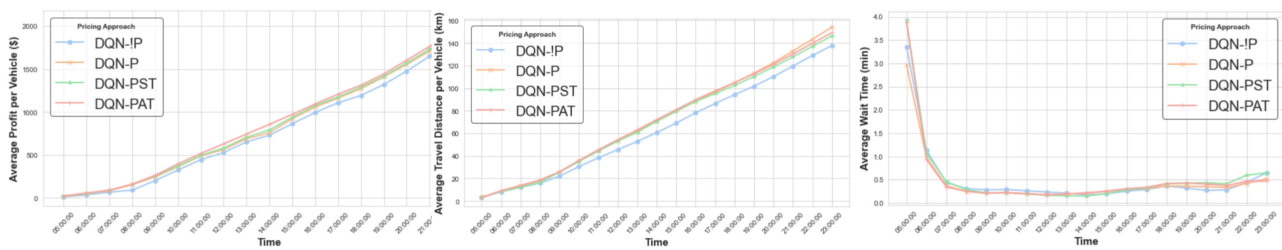
- DQN-A* [120]: this method employs the A* routing algorithm for finding the shortest route in the road network.
- DQN-OSRM [121, 198]: this method utilizes the OSRM routing algorithm for generating the shortest route.
- **DQN-IRE** (ours): this is our routing method which integrates OSRM and A* for computing the shortest route.

3.3.7 Results: The comparative study, as showcased in Figure 17a, reveals that DQN-DC significantly outperforms the baselines by yielding higher profits. Specifically, DQN-DC achieves approximately 20% and 3% more profit than DQN-!C and DQN-SC, respectively, underscoring its superior capability in optimizing economic returns for vehicle operations within the ridesharing framework. The adoption of advanced demand prediction models, particularly the diffusion convolution model (DQN-DC), is pivotal in this enhancement. DQN-DC's ability to efficiently process and interpret the latent spatial structures of graph-represented road networks results in more accurate demand forecasting compared to the traditional convolution model employed by DQN-SC. This strategic incorporation of graph-based learning techniques into DQN-DC not only optimizes profit generation but also addresses complex routing challenges inherent in dynamic urban environments. While Figure 17b indicates that DQN-DC incurs a slightly higher average travel distance compared to DQN-!C, the substantial increment in profits validates the effectiveness of this approach, demonstrating that the minor increase in operational range is a worthwhile trade-off for the financial benefits realized. Additionally, the operational efficiencies gained through our model are further evidenced by reductions in customer waiting times, as illustrated in Figure 17c. DQN-DC cuts down waiting times by 34% relative to DQN-!C, enhancing customer satisfaction by ensuring timely pickups. Such prompt service not only improves user experience but also boosts the system's overall throughput.



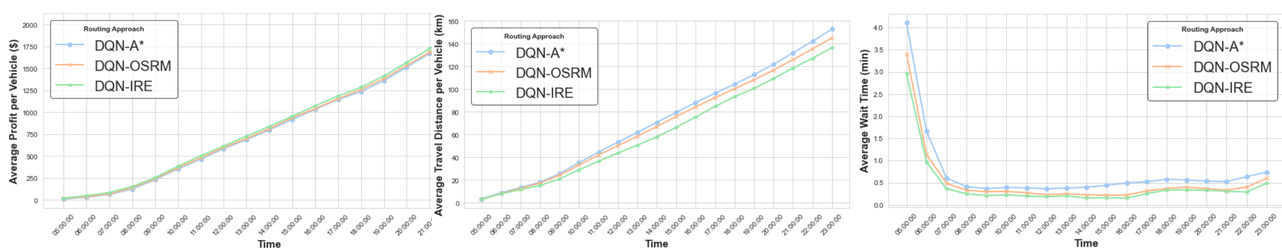
(a) Vehicle profit. (b) Travel distance. (c) Wait time.

Figure 17. Performance evaluation of the proposed framework and the baselines with emphasis on demand prediction.



(a) Vehicle profit. (b) Travel distance. (c) Wait time.

Figure 18. Performance evaluation of the proposed framework and the baselines with emphasis on pricing.



(a) Vehicle profit. (b) Travel distance. (c) Wait time.

Figure 19. Performance evaluation of the proposed framework and the baselines with emphasis on routing.

In Figure 18a, it can be seen that our DQN-PST strategy attains about 7% and 2% more profit than DQN-!P, and DQN-P, respectively. Moreover, our DQN-PAT strategy achieves about 10% and 4% more profit than DQN-!P, and DQN-P, respectively. These findings suggest that the profit improvements of the DQN-PST strategy can be attributed to the inclusion of our adaptive tipping strategy within the DQN-PAT framework. In Figure 18b, the no pricing strategy (DQN-!P) shows consistently lower travel distance compared to the pricing strategies (DQN-P, DQN-PST, DQN-PAT). However, DQN-!P exhibits lower profit compared to the pricing strategies. The customers' wait times are not significantly influenced by the chosen pricing strategy, as illustrated in Figure 18c.

Figure 19 illustrates a comprehensive performance evaluation of our proposed routing strategy, DQN-IRE, against established baseline methodologies, specifically DQN-A* and DQN-OSRM. As detailed in Figure 19a, DQN-IRE consistently outperforms these baselines, generating approximately 3% and 4% higher profit margins compared to DQN-A* and DQN-OSRM, respectively. This superior performance underscores the effectiveness of DQN-IRE in optimizing routing strategies more efficiently. Further analysis, as shown in Figure 19b, reveals that DQN-IRE significantly reduces travel distances by about 13% compared to DQN-A* and 9% compared to DQN-OSRM. This reduction not only implies lower operational costs but also less time spent on the road, which directly contributes to the system's efficiency. As depicted in Figure 19c, the optimization strategy employed by DQN-IRE also contributes to reduced waiting times for customers, with decreases of 4% and 2% when compared to DQN-A* and DQN-OSRM, respectively. This improvement in service speed significantly boosts customer satisfaction and service reliability.

3.3.8 Conclusion: We proposed an integrated framework to address the challenges of demand prediction, pricing, and routing in ridesharing systems. To improve vehicle dispatch decisions, we employed DCNN layers for future demand prediction, leveraging the road network's inherent graph structure to learn more effective feature representations. For pricing, we introduced a dynamic strategy that incorporates stochastic travel times, ensuring a fair and realistic fare calculation that accounts for the varying traffic conditions on road networks. Additionally, we integrated an adaptive tipping mechanism to enhance driver engagement and motivation. To provide reliable real-time routing information, we developed an integrated routing engine that combines the strengths of the OSRM and the A* algorithm. Comprehensive experiments using a real-world, publicly available New York City taxi dataset demonstrated the effectiveness of the proposed framework. The results show that our approach improves vehicle profitability by up to 20%, reduces the average travel distance by up to 13%, minimizes average idle time by up to 10%, cuts passenger waiting time to under one minute, and achieves more efficient fleet utilization compared to baseline methods.

3.3.9 Future Research Needs: Future research will expand on the demand prediction model by incorporating recurrent neural networks to capture both spatial and temporal dependencies in demand flow, further enhancing the framework's predictive capabilities.

3.3.10 Relevance to NCDOT This task is directly relevant to NCDOT's strategic goals of improving mobility, enhancing system efficiency, supporting emerging transportation technologies, and preparing for future CAV-enabled transportation systems. The proposed distributed ridesharing framework provides NCDOT with a scalable and data-driven decision-support tool for evaluating and implementing intelligent shared mobility solutions across urban and suburban corridors. By integrating advanced demand prediction, dynamic pricing, and optimized routing within a distributed reinforcement learning architecture, the framework enables more efficient fleet utilization, reduced congestion, shorter passenger waiting times, and improved operational profitability. These capabilities are particularly valuable for first/last-mile connectivity, public transit integration, and potential deployment of CAV-based shared fleets. Furthermore, the framework supports scenario testing and pilot program design, allowing NCDOT to assess the operational, economic, and traffic impacts of ridesharing services before large-scale implementation. Ultimately, this work equips NCDOT with a technically rigorous foundation for advancing smart mobility initiatives while improving transportation efficiency, sustainability, and service reliability throughout North Carolina.

3.4 Task 3: Quantifying the Effects of CAVs on Traffic Operations at Roundabout by Simulation Analysis

3.4.1 Background: Roundabouts are widely implemented in modern traffic networks because they promote continuous vehicle flow and provide substantial safety benefits [106]. By reducing conflict points and operating at lower speeds than signalized intersections, roundabouts significantly decrease crash frequency and severity. However, despite these advantages, their performance can deteriorate under high traffic demand. Since roundabout entry is governed by gap acceptance behavior, operations become highly dependent on driver judgment, leading to variability in delays and potential congestion during peak conditions. Enhancing intersection performance without modifying geometric design remains a central challenge in traffic engineering. The emergence of CAVs offers new opportunities to address this issue. Through vehicle-to-everything (V2X) communication and advanced onboard computation, CAVs can coordinate movements, share real-time information, and optimize trajectories. Previous research has demonstrated the effectiveness of CAV-based control strategies at signalized intersections, where optimizing signal timing and vehicle trajectories can significantly reduce delays and improve throughput [73] [118] [78]. In contrast, the application of CAV technologies at roundabouts remains less explored, particularly under mixed-traffic conditions. Because roundabout entry relies on stochastic gap acceptance, hesitant human-driven vehicles (HVs) can limit the potential efficiency gains of CAVs. Even when CAVs are capable of precise trajectory control, their benefits may be constrained if they operate behind HVs or interact with unpredictable driver behavior. Therefore, utilizing CAVs to improve overall roundabout performance in mixed traffic is essential. This study aims to quantify the operational impacts of CAVs at a single-lane roundabout using microscopic simulation. Specifically, we propose novel CAV control system where CAVs drive optimally and provide speed guidance to HVs. By modeling CAV trajectory control system and evaluating different market penetration rates, the research assesses changes in delay, throughput, and overall efficiency. The findings provide insights into how increasing levels of connectivity and automation may enhance roundabout performance without requiring physical infrastructure expansion.

3.4.2 Literature Review: Previous studies have investigated CAV control strategies for roundabout operations from different perspectives. Early work by Pérez et al. [126] focused on autonomous vehicle (AV) maneuvering in roundabouts, including lane keeping, lane changing, and turning, using a 3D simulation environment. Nor and Namerikawa [119] proposed an MPC-based control strategy for smooth merging in a simplified two-legged roundabout, considering only a small number of interacting vehicles. Tian et al. [167] introduced a game-theoretic framework to model interactions between an ego AV and a circulating vehicle, incorporating neural networks to predict conservative or aggressive driving behavior. Similarly, Hidalgo et al. [61] addressed single-vehicle AV merging using Bezier-curve-based path generation combined with MPC, while Bosankić and Mehmedović [25] proposed a fuzzy logic speed control framework with V2I coordination for both CAVs and HVs. Although these studies advanced AV maneuvering concepts, they largely ignored realistic multi-vehicle interactions, stochastic HV behavior, demand variability, and systematic performance benchmarking. A separate stream of research has focused on fully autonomous roundabout control using priority-based or First-Come-First-Serve (FCFS) logic. Azimi et al. [16] and Martin-Gasulla and Elefteriadou [98] developed FCFS-based trajectory control frameworks that dynamically adjusted vehicle speeds to avoid conflicts, reporting substantial delay reductions compared to conventional operations. Long et al. [91] extended this concept by assigning right-of-way priorities before optimizing trajectories, achieving significant delay and throughput improvements under fully autonomous conditions. Bakibillah et al. [18] proposed a cloud-based control system to minimize merging time in autonomous roundabouts. However, these approaches rely on fixed or preassigned priority structures and assume fully automated traffic, limiting their applicability in mixed-traffic environments. More recent optimization-based studies, such as Mohebifard and Hajbabaie [103] and Danesh et al. [34], formulated trajectory control problems using point-mass vehicle models and multi-stage optimization frameworks, demonstrating notable efficiency gains under fully autonomous scenarios. Zhao et al. [211] proposed a hybrid FCFS–car-following strategy, while Mohebifard and Hajbabaie [104] extended trajectory optimization to mixed traffic using a mixed-integer nonlinear formulation. Although promising, existing mixed-traffic studies still fall short of utilizing the full benefits of CAVs and quantifying their effects on roundabouts.

3.4.3 Proposed Method: This study develops a nonlinear programming framework to control CAV trajectories in a single-lane roundabout under mixed traffic conditions. Vehicle trajectories are initially formulated in a two-dimensional Cartesian coordinate system, where vehicle position, speed, and acceleration are optimized over a finite prediction horizon T using real-time state information collected through V2V or V2I communication. To reduce computational complexity and improve real-time applicability, the model is transformed into the Frenet coordinate system, which converts the original two-dimensional spatiotemporal problem into a one-dimensional longitudinal formulation along the roundabout reference path. This transformation eliminates the need for vectorized two-dimensional constraints and simplifies collision avoidance, spacing, and kinematic constraints while preserving essential safety and vehicle dynamics relationships. As a result, the reduced formulation enables efficient optimization of longitudinal motion without loss of modeling fidelity. The reduced-order optimization problem is solved using two approaches: First, commercial optimization solvers are utilized to obtain globally optimal solutions. Second, a heuristic-based algorithm is developed to generate near-optimal solutions with significantly reduced computation time, enabling real-time deployment. In addition, the optimization algorithm is embedded within a model predictive control (MPC) framework, where vehicle states are updated at each control step, future trajectories are re-optimized over a receding horizon, and only the first control action is implemented. This structure allows the controller to continuously adapt CAV trajectories in response to evolving traffic conditions and disturbances. Within this framework, CAVs act as mobile controllers by coordinating their motion to create and communicate safe gap opportunities to waiting HVs at roundabout entries. This control mechanism facilitates more efficient merging of HVs, thereby improving overall roundabout performance while maintaining realistic mixed-traffic interactions. The proposed methodology is implemented in PTV VISSIM [130], and its performance is evaluated against a calibrated mixed-traffic baseline consisting of both CAVs and HVs. This comparative analysis enables quantification of the impacts of CAV trajectory control on roundabout operations, including scenarios with and without speed guidance communicated to HVs.

Overall, the proposed control framework generates optimal and safe CAV behaviors in roundabout environments while enhancing mixed-traffic efficiency. The overall framework is illustrated in Figure 20.

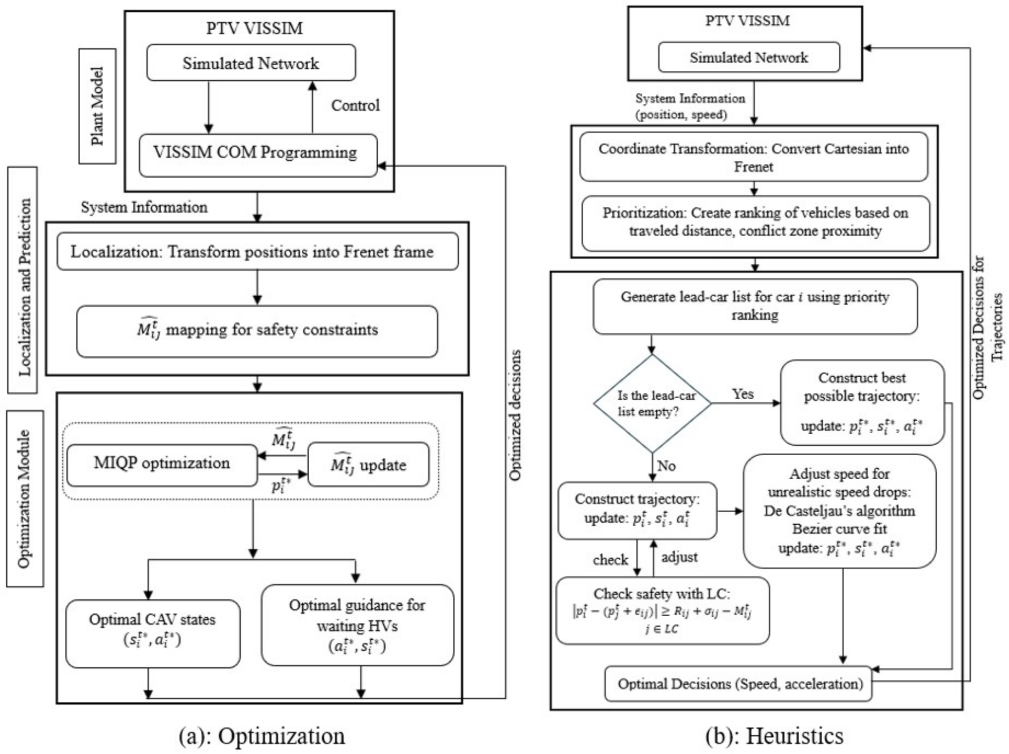


Figure 20. Proposed framework for CAV trajectory control.

3.4.4 Results: A single-lane roundabout with four entry approaches located at the intersection of Hillsborough Street and Dixie Trail in Raleigh is selected as the case study. A microscopic simulation model of the roundabout is developed using PTV VISSIM to evaluate the effectiveness of the proposed CAV control framework and to benchmark its performance against conventional traffic operations. Three primary scenarios are considered for analysis: (i) HV operation (ii) CAV operation (iii) Our proposed control approach. Table 5 summarizes the overall roundabout performance under different demand levels and control strategies, highlighting the operational benefits of CAV-based trajectory control. Across all demand scenarios, both the heuristic-based and optimization-based control approaches substantially outperform the conventional HV and baseline CAV simulations. Results indicate significant improvements in travel time (10%–68%), delay reduction (1%–99%), and throughput (1%–44%), while also minimizing delay variations for minor traffic movements.

For different CAV market penetration rates, the proposed control framework outperforms conventional mixed traffic operation. Table 6 compares optimized control performance with conventional mixed traffic which clearly shows the superiority of cooperative CAV control system.

While optimization-based control has superior performance, the framework requires higher computation times with increasing demand levels. Heuristics-based approach, on the other hand, generates near-optimal solutions to CAV control with significantly less computation time (Figure 21).

Vehicle trajectories (Figure 22) also show improvements from CAVs because CAVs can drive cooperatively without stochasticity and thereby incur less stops and delays.

The gap times for our proposed control (only heuristics-based is shown here) were analyzed and compared to the benchmarks (See Figure 23a). As CAVs communicate and cooperate to achieve maximum performance, shorter headway (1.57 s) is achieved through the proposed control. In terms of critical gap, a value of 2.8 s is achieved for the proposed control as CAVs deterministically decide to enter the gaps communicating with circular CAVs, this results in significant shorter gap acceptance time. Entry capacities of optimal CAV operation also show significant improvement over conventional roundabout operation (Figure 23b). It is important to note here that the capacity values are based on

Table 5. Overall Roundabout Performance Measures

Demand Level	Performance Measure	HV Simulation	CAV Simulation	Heuristics	Optimization
400	Total Travel Time (h)	3.0	2.8	2.3	2.2
	Average Delay (s)	5.1	3.4	0.7	0.1
	Average Speed (mph)	17.3	18.4	23.9	24.7
	Throughput (veh)	381	381	392	389
	Latent Demand (veh)	1	0	0	0
600	Total Travel Time (h)	6.6	5.0	3.4	3.3
	Average Delay (s)	18.5	7.6	0.9	0.2
	Average Speed (mph)	11.5	15.9	23.7	24.2
	Throughput (veh)	557	578	586	586
	Latent Demand (veh)	13	0	0	0
900	Total Travel Time (h)	15.3	14.3	5.4	4.9
	Average Delay (s)	37.1	34.0	2.32	0.2
	Average Speed (mph)	7.9	8.2	22.2	24.4
	Throughput (veh)	605	761	869	870
	Latent Demand (veh)	272	97	0	0
600–300	Total Travel Time (h)	3.2	3.0	2.5	2.4
	Average Delay (s)	6.5	3.3	0.5	0.1
	Average Speed (mph)	17.7	19.0	24.2	24.6
	Throughput (veh)	411	411	434	437
	Latent Demand (veh)	0	0	0	0

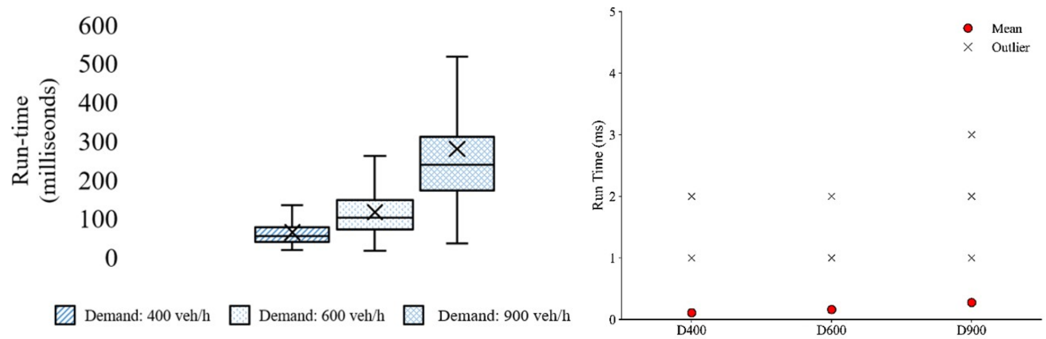
Table 6. Roundabout Performance Measures under Different CAV Market Shares

Demand (veh/h)	Performance Measure	CAV Market Share									
		20%		40%		50%		60%		80%	
		Sim	Opt	Sim	Opt	Sim	Opt	Sim	Opt	Sim	Opt
400	Total Travel Time (h)	2.9	2.7	2.9	2.6	2.9	2.6	2.9	2.5	2.8	2.3
	Average Delay (s)	4.5	4.9	4.3	3.7	4.2	3.7	3.9	3.2	3.7	1.6
	Average Speed (mph)	17.7	19.5	17.8	20.9	17.9	21.0	18.1	21.3	18.3	22.9
	Throughput (veh)	381	385	381	390	381	395	381	388	381	392
	Latent Demand (veh)	1	0	0	0	0	0	0	0	0	0
600	Total Travel Time (h)	6.1	4.2	5.8	4.2	5.7	4.2	5.6	4.1	5.2	3.8
	Average Delay (s)	15.3	5.7	12.7	5.7	12.7	5.7	11.4	5.0	9.1	3.4
	Average Speed (mph)	12.6	19.1	13.5	19.1	13.5	19.2	14.0	19.7	15.1	21.1
	Throughput (veh)	563	581	570	576	564	582	572	583	576	588
	Latent Demand (veh)	10	0	4	0	8	0	0	0	0	0
900	Total Travel Time (h)	15.4	7.0	15.5	7.0	15.5	6.9	15.6	6.6	15.3	6.1
	Average Delay (s)	37.5	9.1	38.0	8.7	38.0	8.6	38.4	7.3	37.8	5.3
	Average Speed (mph)	7.8	16.8	7.8	17.1	7.8	17.1	7.7	18.0	7.8	19.4
	Throughput (veh)	632	856	662	866	681	855	689	868	723	858
	Latent Demand (veh)	244	0	210	0	193	0	180	0	143	0
600–300	Total Travel Time (h)	3.2	3.1	3.1	3.0	3.1	3.0	3.1	2.9	3.0	2.7
	Average Delay (s)	6.1	5.4	5.5	4.9	5.1	4.6	4.3	4.3	3.8	2.5
	Average Speed (mph)	18.0	19.4	18.3	19.8	18.5	20.1	18.6	20.3	18.8	21.9
	Throughput (veh)	411	435	411	439	410	435	411	431	411	437
	Latent Demand (veh)	0	0	0	0	0	0	0	0	0	0

Note: Sim = Simulation; Opt = Optimization.

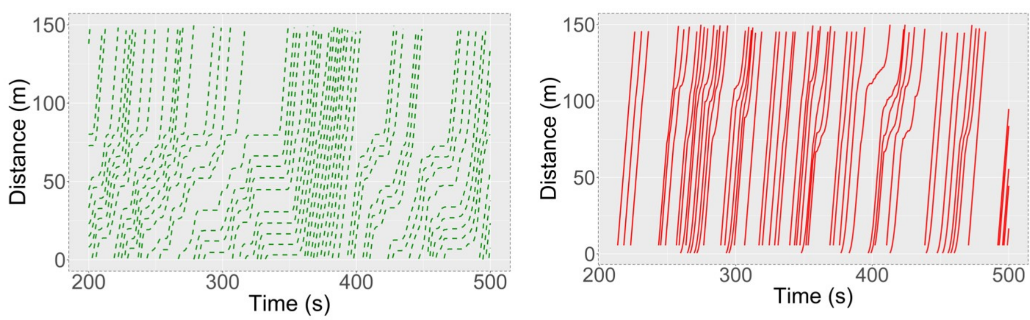
full CAV fleet under our proposed control mechanism.

3.4.5 Conclusion: This study proposed a trajectory control framework for CAVs operating in single-lane roundabouts, in which CAVs function as mobile traffic controllers to optimize vehicle movements and entry decisions while ensuring safety and driving comfort. The framework is formulated as a two-dimensional spatiotemporal optimization model that generates optimal speed and acceleration profiles based on real-time state information and predicted future system states. To address computational complexity, the model is transformed into the Frenet



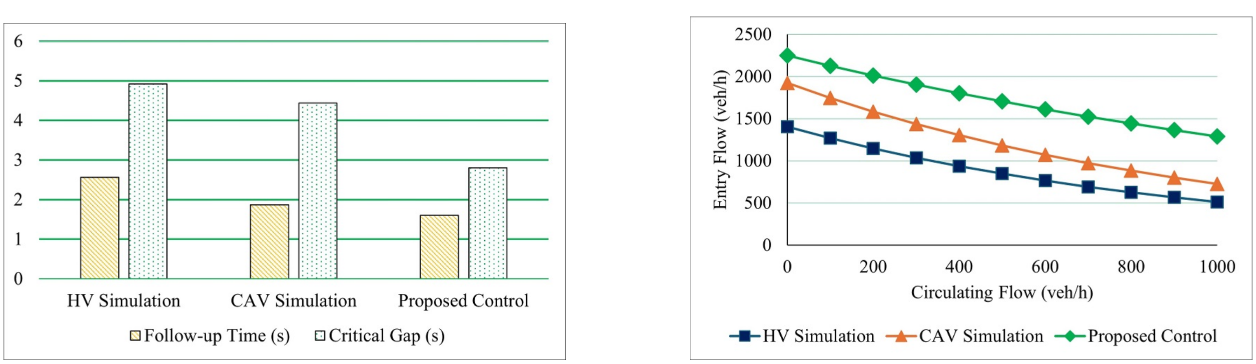
(a) Optimization (b) Heuristics

Figure 21. Computation Time for Different Demand Levels.



a. HV Operation b. Proposed Control (Heuristics)

Figure 22. Vehicle Trajectories.



(a) Roundabout Capacity Parameters. (b) Entry Flows for Different Circulating Flows.

Figure 23. Effects of CAVs on Roundabout Capacities.

coordinate system, reducing the problem to a one-dimensional formulation, and is solved using a model predictive control (MPC) approach. To enable real-time applicability, a trajectory construction heuristic with dynamic vehicle priority ranking is also developed (in addition to optimization-based approach) and embedded within a receding horizon framework, achieving near-optimal solutions with high computational efficiency.

The proposed methodology is evaluated using a calibrated microscopic simulation of a real-world roundabout, where mixed traffic conditions are modeled to reflect realistic driving behavior. Simulation results demonstrate substantial performance improvements across various demand levels, including reductions in total travel time of up to 68%, reductions in average delay of up to 99%, and throughput increases of up to 44%. Unlike conventional roundabout operations that rely on stochastic driver behavior, the proposed framework improves efficiency by both utilizing available gaps more effectively and actively creating gaps through coordinated CAV control. In doing so, the framework combines advantages of unsignalized and signalized roundabout operations while requiring minimal computational effort highlighting strong potential for real-world deployment.

3.4.6 Future Research Needs: While the results are promising, the study assumes ideal communication among CAVs without delays, data loss, or privacy constraints. Future research should investigate the impacts of realistic vehicle-to-vehicle and vehicle-to-infrastructure communication limitations, including latency, bandwidth, and information-sharing constraints. Additional extensions include scaling the framework to multi-lane roundabouts, exploring learning-based predictive control methods for enhanced adaptability under highly dynamic traffic conditions, and conducting full-scale field implementations.

3.4.7 Relevance to NCDOT: This research is relevant to NCDOT as it offers a cost-effective strategy to improve the efficiency and safety of existing roundabouts without requiring major infrastructure changes as demand grows. By leveraging CAVs as mobile traffic controllers, the proposed framework increases capacity, reduces delays, and enhances travel time reliability. The approach aligns with NCDOT's goals in intelligent transportation systems and data-driven traffic management, providing a practical pathway for integrating CAV technologies into North Carolina's growing roundabout network during the transition toward more connected and automated mobility.

3.5 Task 4: Deployment of CAVs to enhance the capacity of roundabout

3.5.1 Background: Roundabouts are increasingly adopted as a traffic management strategy due to their potential to improve safety, reduce delay, and enhance overall traffic efficiency. However, their operational capacity is often limited by driver behavior variability, merging conflicts, and inconsistent gap-acceptance decisions, particularly under mixed traffic conditions. The deployment of CAVs presents a promising pathway to enhance roundabout throughput by enabling coordinated vehicle behavior, reduced reaction times, and predictive trajectory control. Unlike conventional vehicles, CAVs can exchange real-time information such as velocity, position, and intent through V2V and V2I communication frameworks. This connectivity allows coordinated merging, smoother speed adjustments, and optimized entry timing, which collectively contribute to improved traffic flow stability and increased roundabout capacity. Recent advancements in cooperative driving architectures demonstrate that coordinated CAV operation can reduce stop-and-go behavior, minimize unnecessary braking events, and improve safety margins during entry and circulation maneuvers.

Within this task, the focus is placed on enabling cooperative operation between multiple CAVs navigating a roundabout environment using a scalable communication architecture. A dedicated server-based connectivity framework was implemented to facilitate reliable data exchange between vehicles and a centralized control application. The deployed system integrates on-board 5G communication modules, a web-based application hosted on an Apache2 server, and Cloudflare-supported networking to allow real-time data transfer between circulating and approaching vehicles. By transmitting GNSS position and velocity information to a centralized control algorithm, the system enables coordinated decision-making, such as managing entry timing when vehicles are already circulating within the roundabout. Thus, the project establishes the foundation for evaluating how cooperative CAV deployment and reliable communication infrastructure can contribute to enhanced operational efficiency and capacity improvements at roundabouts.

3.5.2 Literature Review: Prior research on automated roundabout systems has progressed from isolated vehicle-level control toward coordinated multi-vehicle strategies supported by communication frameworks. Recent studies emphasize structured sequencing, speed harmonization, and connectivity-assisted decision-making to regulate interactions at entry and circulation zones. These approaches demonstrate that coordinated vehicle control can reduce delay and increase throughput compared to conventional human-driven operations. Early investigations focused primarily on motion control and interaction-aware planning to address curved geometries and merging dynamics.

Over time, research expanded to integrate reliable low-level path tracking with higher-level coordination mechanisms capable of managing multi-vehicle interactions. This evolution underscores the importance of coupling robust vehicle control with centralized or distributed communication frameworks to enable safe and efficient cooperative roundabout operation. More recent work explicitly explores cooperative CAV behavior using communication-enabled architectures. Cooperative roundabout control strategies show that connected vehicles can dynamically adjust entry timing and speed profiles to mitigate congestion and improve mobility performance [180]. Similarly, connected mobility frameworks leveraging 5G communication and edge computing demonstrate enhanced traffic flow and passenger comfort through real-time centralized coordination [129]. These findings are consistent with the communication architecture adopted in this project, where vehicle telemetry is transmitted through a dedicated server infrastructure to support cooperative decision-making.

In parallel, machine-learning and reinforcement-learning approaches have been investigated to optimize automated vehicle behavior in roundabout environments. Multi-agent deep reinforcement learning methods enable vehicles to learn cooperative merging and circulation strategies that improve traffic efficiency [111]. Trajectory optimization techniques developed for mixed traffic scenarios further indicate that increasing CAV penetration can reduce travel time and stabilize traffic flow dynamics [105]. Collectively, these studies highlight the role of connectivity-driven coordination and predictive control in enhancing roundabout performance. Despite these advancements, much of the existing work remains limited to simulation-based validation, with comparatively fewer real-world demonstrations integrating scalable communication infrastructure and multi-vehicle coordination. The present project addresses this gap through deployment of a dedicated server-based communication system supported by 5G networking, enabling real-time data exchange between multiple CAVs operating in a physical roundabout. By combining cooperative connectivity with experimental implementation, this work advances the practical evaluation of connected automated vehicles for enhancing roundabout capacity and operational performance in realistic driving conditions.

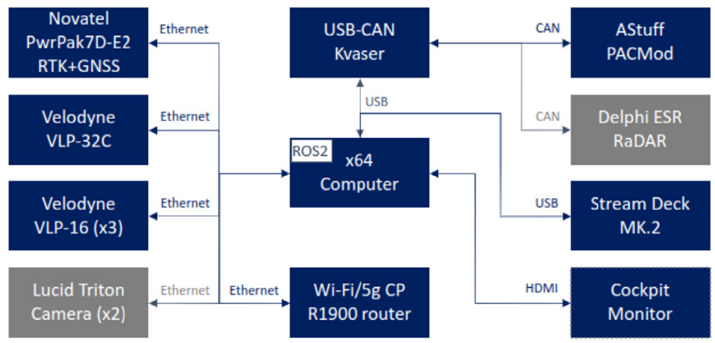
3.5.3 Proposed Method and Results:

3.5.3.1 Experimental Testbed: This project utilized Polaris GEM e6 electric vehicles as the experimental platform for real-world roundabout (Figure 24) deployment at the NC A&T test track and cooperative control evaluation. The Polaris GEM e6 is a six-passenger, low-speed electric vehicle capable of a top speed of 40 km/h, making it well-suited for campus and suburban autonomous driving scenarios. Each vehicle is powered by a 48V AC induction electric motor delivering 6.5 kW (8.7 HP) of continuous power, regulated by a Sevcon 450A AC controller, and supported by a lithium-ion battery pack providing an operational range of at least 20 km. The drivetrain incorporates direct front-wheel drive with regenerative braking for improved energy efficiency. Three such vehicles were developed and deployed as the Aggie Auto Shuttles at North Carolina A&T State University, forming the fleet used in both the public road demonstration and the roundabout cooperative control experiments. A comprehensive technical article detailing the system architecture, field validation, and public roadway deployment of the Aggie Auto Shuttles has been published in [100], providing an in-depth account of the platform development and operational insights.

Figure 24. Experimental roundabout test site used for CAV deployment and cooperative operation experiments.

Sensor Suite: A comprehensive sensor suite was integrated on each vehicle to enable perception, localization, and communication in semi-urban driving environments, as depicted in Figure 25a. The primary perception sensor is a Velodyne VLP-32C LiDAR(1), mounted in an elevated position at the top center of the vehicle using aluminum frames to facilitate environmental perception at medium and long ranges. Three additional Velodyne VLP-16 LiDAR (2) units are mounted on the roof rack above the windshield, one each on the left, center, and right, to mitigate blind spots at shorter ranges. For localization, a NovAtel PwrPak7D-E2 GNSS+INS receiver with dual roof-mounted antennas (3) provides high-precision position and orientation data, including Real-Time Kinematic (RTK) corrections from public ground stations. Two Lucid Triton IMX265 cameras (4) with 12 mm and 16 mm focal-length lenses are installed on the front of the roof rack to provide visual redundancy. A Delphi ESR radar (5) sensor mounted on the front bumper provides mid-to-long-range object detection capability [101]. Finally, a Cradlepoint R1900 router integrated with a MAKO 5G dome antenna (6) enables 5G cellular connectivity and Wi-Fi communication for real-time vehicle-to-server data exchange.

(a) Aggie Auto and sensor suite



(b) Hardware architecture of the Aggie Auto Shuttle platform showing sensor integration, ROS2 onboard computing, drive-by-wire interface, and 5G connectivity

Figure 25. Experimental testbed of Aggie Auto Shuttle

Hardware Architecture: All sensors and communication devices are connected to an industrial-grade onboard computing unit, as shown in Figure 25b. The computer (OnLogic K800) is equipped with an Intel Core i9-12900E (16-core/24-thread) CPU, an NVIDIA RTX A4000 GPU, and a 1 TB NVMe M.2 2280 SSD, providing the computational resources necessary for real-time sensor processing and autonomous driving functions. The LiDAR units, GNSS+INS receiver, cameras, and cellular router are interfaced via Ethernet connections. A Kvaser USB-to-CAN converter links the computer to the Delphi ESR radar and the Platform Actuation and Control Module (PACMod) Drive-By-Wire (DBW) system for low-level vehicle actuation. An Elgato Stream Deck MK.2 serves as the human–machine interface (HMI), enabling operators to issue commands for trip destinations, driving mode selection, DBW configuration, localization reset, and system startup. Power electronics rely on commercial off-the-shelf components integrated to meet the operational requirements of the sensor suite, computing platform, and vehicle actuators.

Software Stack and Autoware Integration: The vehicles operate using the Autoware Universe open-source automated driving stack built on ROS2, providing a full pipeline for localization, perception, planning, and control (Figure 26). High-definition maps are generated using lidar inertial odometry via smoothing and mapping (LIO-SAM) [148] by fusing VLP-32C LiDAR and GNSS+INS data into 3D point cloud (PCD) maps, followed by semantic annotation in Lanelet2 format using Vector Map Builder and validation through Java OpenStreetMap (JOSM) Editor. Localization relies primarily on LiDAR-based `ndt_scan_matcher`, refined by `ekf_localizer`, with GNSS providing initialization and fallback capability. Object detection and tracking utilize `center_point`, `euclidean_cluster`, and `multi_object_tracking`, while future motion prediction is performed using `map_based_prediction`. Mission and behavior planning are handled by `mission_planner`, `behavior_path_planner`, and `behavior_velocity_planner`. Motion planning employs `obstacle_cruise_planner` and `motion_velocity_smoother`, and low-level control is executed using `mpc_lateral_controller` for steering and `pid_longitudinal_controller` for speed regulation.

In addition to the onboard autonomy stack, vehicle state information such as GNSS position and velocity is shared with an external server through a ROS Bridge WebSocket interface, as illustrated in the figure. A Node.js middleware layer serializes relevant ROS2 topics and enables bidirectional communication with a centralized web-based control algorithm. The server computes supervisory commands, such as maximum allowable velocity within the roundabout control zone, which are then transmitted back to the vehicle and integrated into the local planning and control modules without modifying the core trajectory generation logic.

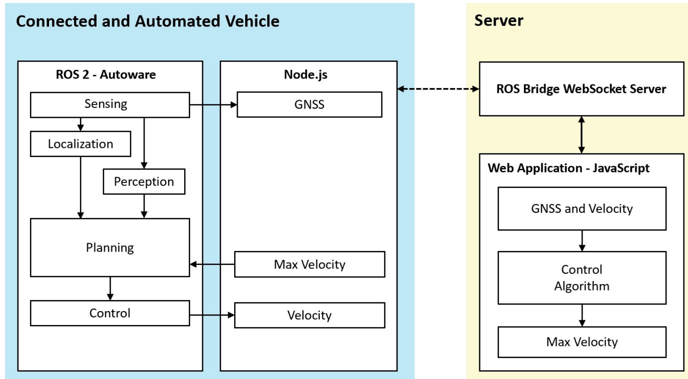


Figure 26. Software stack and integration outline of Autoware to Aggie Auto Shuttles.

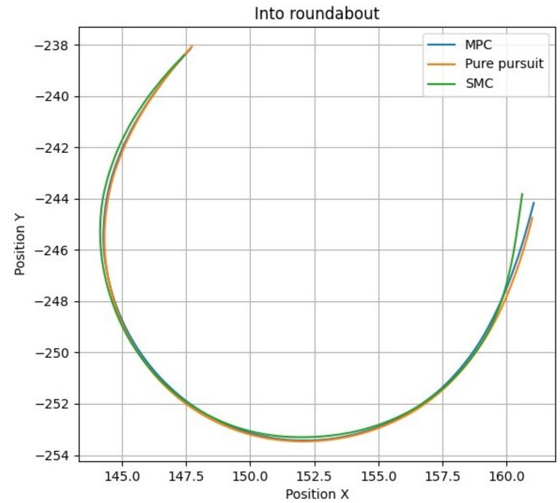
3.5.3.2 Robust Control for Handling Roundabouts by an Automated Vehicle: Each vehicle is equipped with advanced control technique for handling sharp curvatures of small roundabouts. As part of this task, a Sliding Mode Controller (SMC) was designed and experimentally validated as a robust control strategy to handle the sharp curvature and dynamic operating conditions commonly encountered in small roundabouts. Roundabouts impose significant demands on path-tracking controllers due to continuously varying curvature, low-speed maneuvering, and sensor uncertainty present in real-world deployments. While standard controllers such as Pure Pursuit (PP) and Model Predictive Control (MPC) are effective for smooth trajectories, their performance may degrade in tight, high-curvature segments. Therefore, a more robust control approach was developed and its performance was assessed in comparison with these benchmark controllers.

The SMC follows a formulation in which path tracking is based on a kinematic bicycle model expressed in path coordinates. The control state includes lateral tracking error and its rate of change, as well as heading error and its rate of change. The vehicle model is reconfigured through the addition of velocity-proportional feedback gains to enhance energy dissipation and promote convergence toward zero tracking error. Lyapunov-based stability analysis, including both local and global assessments, confirms that the reconfigured system is asymptotically stable across a broad range of operating conditions. This stability property is particularly important for roundabout traversal, where abrupt curvature transitions and speed variations are unavoidable. All design details, theoretical development, and implementation considerations of the adopted Sliding Mode Control method are comprehensively documented in [99] by Matute et al. To improve practical implementation, the controller incorporates mechanisms to reduce oscillatory steering behavior while maintaining robustness to disturbances and sensor noise. Speed-dependent adjustments allow the controller to balance smoothness and responsiveness throughout the vehicle’s operating range, from entry deceleration through circular traversal to exit acceleration. In addition, predictive elements based on the vehicle model are included to compensate for actuation delays in the drive-by-wire system, improving responsiveness during rapid curvature transitions.

The performance of the SMC controller in the roundabout scenario is assessed relative to two benchmark controllers, Pure Pursuit (PP) and Model Predictive Control (MPC), both of which are natively integrated into the Autoware autonomous driving software stack. Figure 27b presents the XY trajectories of all three controllers navigating into the roundabout (aerial view is shown in Figure 27a). Qualitative inspection of the trajectories reveals that the SMC produces a smoother and more geometrically consistent arc through the roundabout, adhering more closely to the circular curvature of the reference path. In contrast, both PP and MPC exhibit slight deviations, particularly at the entry and exit transitions where the curvature rate of change is highest. The more rounded shape of the SMC trajectory is attributed to its adaptive velocity-dependent boundary layer and predictive state compensation mechanisms, which enable tighter curvature tracking without the overshoot or under-correction artifacts visible in the competing approaches.

3.5.3.3 Cooperative Control of CAVs for Handling Roundabouts: This project utilizes three GEM-E6 vehicles and equip them with connectivity and communication capabilities, so that they can cooperate and negotiate at roundabouts and implement the developed framework under Task 3.

(a) Annotated aerial view of the roundabout showing entrance, stop line location, and exit region used for cooperative vehicle coordination.



(b) Comparative roundabout trajectories of MPC, PP, and SMC, illustrating improved curvature adherence and smoother path tracking with the SMC approach.

Figure 27. Aerial view of the roundabout and controller performance evaluation

The proposed architectural framework implements a centralized ROS Bridge WebSocket Server to enable bidirectional, real-time communication between multiple CAV clients and a web-based roundabout control algorithm. The experimental roundabout environment used for deployment is shown in Figure 24, where the circulating path and entry regions provide a controlled setting for evaluating cooperative vehicle coordination. An annotated aerial view of the test site in Figure 27a highlights the entrance, exit, and designated stop-line location used to regulate vehicle entry into the roundabout. These physical features define the operational boundaries for the cooperative control strategy, where approaching vehicles must adjust their behavior based on the state of vehicles already circulating within the roundabout.

Each CAV client operates a localized Automated Driving System (ADS) within a ROS2 environment to manage low-level actuator and sensor interfaces through topic-based communication. The vehicles execute path-following and motion control locally, while external coordination commands are handled through a middleware communication layer. A Node.js interface running on each CAV serializes ROS2 topic messages into JSON format, allowing telemetry such as velocity and GNSS position to be transmitted over the 5G network. On the server side, a JavaScript-based web client built with the Robot Client Library for Node.js (rclnodejs) connects to the centralized ROS Bridge WebSocket Server and accesses the aggregated vehicle data pool. This architecture allows the web application to execute coordination algorithms and send control commands back to the vehicles in real time. The connectivity between server and clients through the WebSocket interface is illustrated in Figure 28, which shows the integration of ROS2 topics, Node.js middleware, and web-based control logic.

In this deployment, the centralized server is hosted at North Carolina A&T State University's Autonomous Vehicle Laboratory, where the WebSocket port is exposed through accesslabgateway.com/8443 to enable secure connectivity for both CAV clients and web application interfaces. As shown in Figure 29, each CAV is equipped with a Cradlepoint R1900 router and a MIMO antenna to maintain reliable 5G communication during real-world operation. The vehicles continuously transmit velocity and GNSS position data to the server, allowing the web-based control algorithm to monitor their relative positions within the roundabout environment defined in Figure 24. Based on this information, the algorithm computes a maximum allowable velocity command that regulates vehicle behavior at the roundabout entry, ensuring that approaching vehicles remain stopped at the designated stop line until a safe entry gap is available.

Two-Vehicle/Multi-Vehicle Testing (Placeholder): [To be updated upon completion of full cooperative testing results.] The forthcoming results (Figure 30 and 31) will focus on two-vehicle and multi-vehicle experiments designed to evaluate cooperative behavior under realistic roundabout entry and circulation conditions. These experiments will assess the effectiveness of the centralized web-based coordination algorithm and the server-based communication architecture in regulating vehicle speed while maintaining stable path-following performance through interaction with the onboard vehicle control system. Speed profiles, GNSS trajectories, and control command exchanges will be analyzed to evaluate cooperative performance and potential capacity enhancement effects.

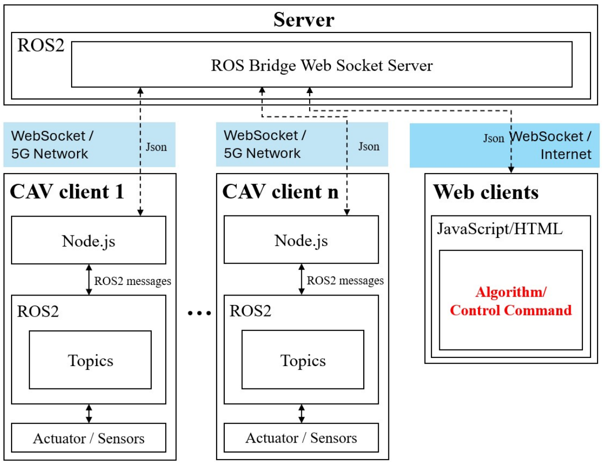


Figure 28. ROS2–WebSocket integration framework illustrating Node.js client interface, ROS Bridge server, and web-based control algorithm for real-time coordination.

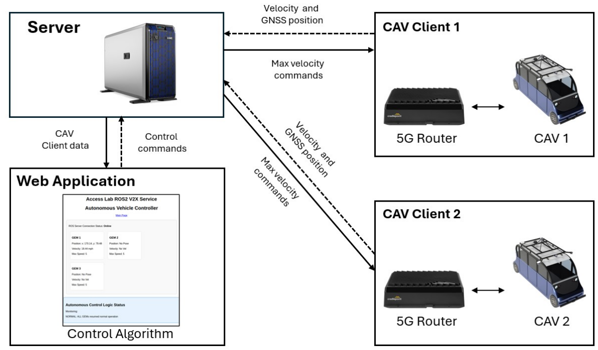


Figure 29. System-level communication architecture showing centralized server, web application, and bidirectional data exchange between multiple CAV clients via 5G connectivity.

Video Demonstration (Placeholder): A recorded video demonstration of the cooperative roundabout operation will be included here upon final compilation. The video will illustrate real-time server coordination, vehicle entry regulation at the stop line, and multi-vehicle interaction within the roundabout environment.

figures/Thrust3-Task4/f5_2-v_testing.jpg

Figure 30. Results: two-vehicle testing scenario.

figures/Thrust3-Task4/f5_3-v_testing.jpg

Figure 31. Results: three-vehicle testing scenario.

3.5.4 Conclusion: This task demonstrated the successful real-world deployment of a centralized, server-based communication and coordination framework to support cooperative CAV operation within a physical roundabout environment. The implemented architecture integrated ROS2-based onboard vehicle control systems with a WebSocket-enabled centralized server hosted at North Carolina A&T State University, enabling real-time bidirectional communication through 5G connectivity. Single-vehicle testing validated reliable telemetry transmission, accurate execution of remotely issued speed constraints, and stable integration between the centralized coordination algorithm and onboard PID/MPC controllers. The results confirm that the proposed framework can dynamically regulate vehicle speed at designated control zones, such as the roundabout entry while preserving trajectory tracking performance. The deployment establishes a functional foundation for cooperative multi-vehicle coordination and provides practical evidence that centralized communication infrastructure can support controlled roundabout entry behavior. Overall, this work advances the transition from simulation-based coordination strategies to real-world implementation, demonstrating the feasibility of scalable, connectivity-enabled CAV deployment for enhancing roundabout operational performance.

3.5.5 Future Research Needs: Although the deployment results demonstrate the feasibility of centralized cooperative CAV coordination at roundabouts, additional research is needed to support large-scale implementation. Future work should evaluate system performance under higher traffic volumes, mixed traffic conditions, and varying CAV penetration rates to assess scalability and robustness. Further investigation of communication reliability, including latency, packet loss, and cybersecurity considerations in 5G and V2X environments, is also recommended.

Expansion to multi-lane roundabouts and diverse geometric configurations should be pursued, along with quantitative assessment of capacity, delay, travel time reliability, and safety surrogate measures. Finally, pilot testing on public roadways in coordination with NCDOT will be essential to validate operational readiness and inform broader deployment strategies.

3.5.6 Relevance to NCDOT: This research supports NCDOT's goals in intelligent transportation systems and connected mobility by demonstrating a practical, cost-effective approach to improving roundabout operations without major infrastructure modifications. The proposed framework leverages coordinated CAVs and 5G-enabled communication to regulate entry behavior, enhance traffic flow stability, and increase potential capacity at existing roundabouts. Designed for real-world deployment using commercially available networking hardware and scalable web-based platforms, the system provides an implementation-ready prototype suitable for pilot testing within North Carolina's expanding roundabout network. By advancing cooperative CAV strategies from simulation to field validation, this task establishes a clear pathway toward future public deployment and broader integration of connected and automated mobility solutions.

3.6 Task 5: Development of a Cloud-based Ride-sharing Application Software for the NC-CAV Testbed

3.6.1 Background: The introduction of autonomous vehicles into a public community requires more than just smart sensors. It requires trust and reliable communication. The NC-CAV Testbed needed a way to bridge the gap between our cutting-edge shuttles and the passengers waiting at the curb. We needed a central nervous system to coordinate the fleet. This system had to ensure safety, manage schedules, and give riders the confidence that a vehicle would arrive when promised. Our primary goal was to create a functional, dependable service that the public would want to use.

We looked to the industry leaders for inspiration. Commercial apps have set the standard for how people hail rides today. We learned valuable lessons from their user interfaces and booking flows. However, these platforms are designed as closed loops. They could not offer us the direct control we needed to manage a specialized autonomous fleet. We could not simply plug our vehicles into their networks. To solve this, we developed our own cloud-based application. This approach gave us the freedom to design a service that fits our specific operational needs. It allows us to manage the daily logistics of the shuttles while simultaneously gathering the deep insights needed to advance transportation research.

3.6.2 Literature Review: We conducted a review of the current shared mobility landscape to inform our development. We examined general ride-hailing services like Uber and Lyft. We also analyzed micro-transit platforms such as Via and RideCo [93, 173]. The micro-transit model was particularly relevant to our project. It uses dynamic routing to serve multiple passengers with a single vehicle. This approach often uses designated pickup points instead of door-to-door service [138, 179]. This aligns with our operational goals for the autonomous shuttle fleet.

We used these commercial applications as key learning tools. They provided a benchmark for user experience and system design. We studied how they present ride options and confirm bookings. We also observed the importance of real-time map tracking for user trust. Additionally, we noted the efficiency of their "block-to-block" routing logic. This method reduces detour time and increases service capacity. We adopted these best practices to ensure our application would be intuitive for the public.

Despite their operational excellence, commercial platforms function as closed systems. They act as "black boxes" to external researchers. They do not allow us to modify their routing algorithms to test new theories. We also cannot access the granular telemetry data required for our traffic studies. This lack of transparency limits their utility for scientific research. Task 5 addresses this by building a comparable, open platform. It delivers the necessary user features while providing the architectural access needed to validate our specific optimization models [146].

3.6.3 Proposed Method

System Architecture: We designed the platform to be robust and scalable. We chose a cloud-native architecture (Figure 32). This means the system lives on remote servers rather than on a single local computer. This setup allows the application to handle many users at once without slowing down. We used a microservices approach. This breaks the application into smaller, independent parts. One part handles user logins, another manages the database, and another tracks vehicle locations. If one part needs an update, we can fix it without stopping the entire system. This modularity is essential for a research testbed where we frequently test new features.

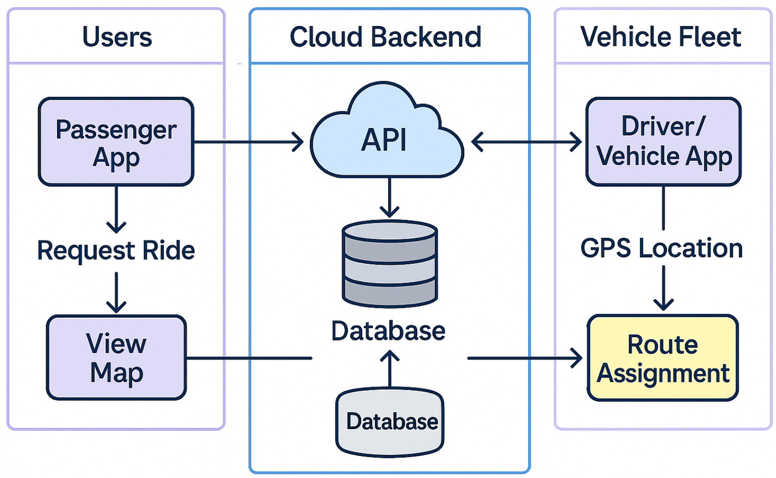


Figure 32. High-level System Architecture Diagram

Key Software Components: The software suite connects three distinct groups of users through specific interfaces:

- Passenger Mobile App: This is the public face of the project. We built it for iOS, Android, and web browsers to ensure accessibility. The design focuses on simplicity. Users can sign up, view the service area, and book a ride with a few taps. It provides real-time updates so riders always know when their vehicle will arrive. It features a **Map Interface** for selecting locations (Figure 33) and a **Navigation Drawer** for accessing settings (Figure 34).
- Driver/Vehicle Interface: This tablet-based app sits inside the shuttle. It guides the safety driver or the autonomous system. It displays the current route and notifies the vehicle when a new passenger is assigned. It acts as the bridge between the digital route and the physical road.
- Administrative Dashboard: This is the control center for the research team. It provides a "bird's-eye view" of the entire operation. Researchers can see active rides, monitor fleet health, and download system logs. It gives us the power to pause operations or adjust settings in real-time.

Data Flow and Routing Logic The system handles a ride request through a logical sequence of steps (see Table 7). First, a user opens the app and requests a ride. The app sends this request to our cloud server. The server acts as the traffic controller. It runs a **Routing Engine** to make decisions.

For this implementation, we used a queue-based algorithm. The engine looks at the list of waiting passengers. It also checks the current direction of each vehicle. It tries to match the new request with a vehicle already moving in that direction. This minimizes detours and keeps the service efficient. Once the engine finds a match, it updates the vehicle's route. Simultaneously, it sends a confirmation to the user. The app then tracks the vehicle in real-time, creating a seamless loop of information between the rider, the cloud, and the shuttle.

3.6.4 Results

Testing Context We conducted the validation in two rigorous phases. First, we used a simulation environment to test the logic safely. This allowed us to run many scenarios without risking physical vehicles. Second, we deployed the software on the autonomous shuttle fleet for a one-week field test. We operated in designated zones at the North

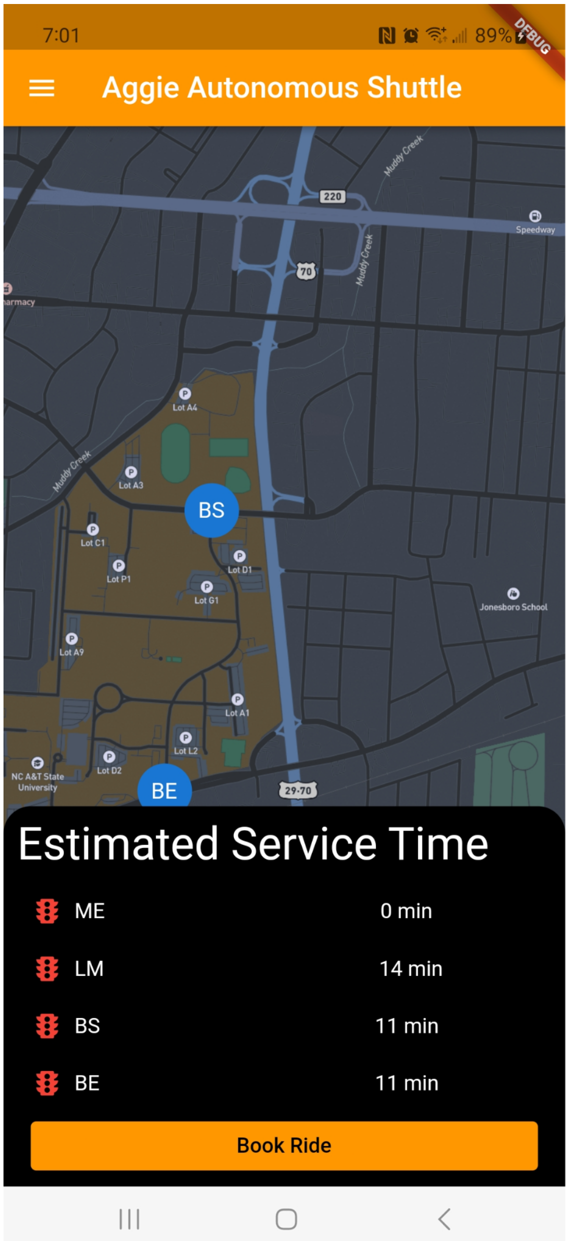


Figure 33. Map-Based Ride Booking Interface in the Passenger Mobile App

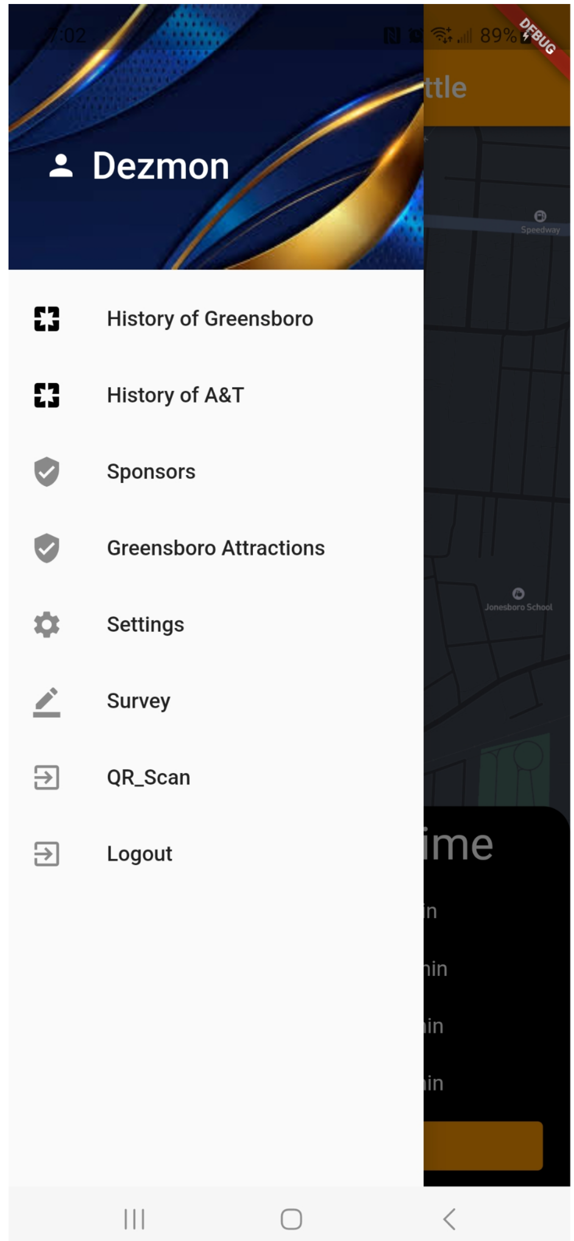


Figure 34. Navigation Drawer Menu for Accessing App Settings

Carolina A&T State University campus and the downtown area. This real-world setting exposed the system to actual network conditions and physical obstacles, providing a true test of its reliability.

System Performance The technical performance of the software met all operational targets. The cloud backend maintained high uptime throughout the trial, which assures the service was always available to users. We monitored the API latency, which is the time it takes for the app to talk to the server. The latency remained low, resulting in a snappy and responsive user interface. The booking rate was 100% successful for valid requests. These results confirm that the microservices architecture is stable and ready for continuous deployment.

Operational Metrics and Key Learnings The simulation phase demonstrated the robustness of the queue-based vehicle assignment algorithm. Ride requests were reliably matched with available vehicles based on queue position and direction of travel, confirming the correctness of the routing logic outlined in the methods section. Across more

Table 7. Functionality of Key Software Modules

Component	Primary User	Key Functions & Responsibilities
Passenger App	General Public	• Account creation and secure login • Real-time ride booking (pickup/drop-off) • Live vehicle tracking on interactive map
Driver Interface	Shuttle Operator	• View assigned route and schedule • Turn-by-turn navigation • Passenger boarding confirmation
Admin Dashboard	Researchers / Staff	• Monitor real-time fleet status • Manually override routes (if needed) • Export data logs for analysis
Routing Engine	System (Automated)	• Process ride requests in real-time • Match passengers to vehicles (Queue Algorithm) • Calculate Estimated Time of Arrival (ETA)

than 50 simulated ride requests, the system consistently assigned vehicles in under 2 seconds on average. This low latency is essential for maintaining responsiveness and preventing user frustration.

A major finding from the field test was the effectiveness of the fixed-terminal approach. Rather than the initial assumption of door-to-door service, the system adopted designated pickup and drop-off points aligned with the existing shuttle operation. This shift significantly simplified routing for the autonomous system while also reducing passenger confusion.

The field test further highlighted the importance of real-time tracking as part of a user-centered application design. Passengers were provided with precise pickup and drop-off locations along with live map updates, which reduced waiting anxiety and increased confidence in the service. This transparency was complemented by built-in feedback tools within the application. A post-ride rating feature captured overall user satisfaction, while the in-app survey collected more detailed qualitative feedback. Together, these features supported a clearer understanding of user reactions and community needs, reinforcing the role of the application in guiding service improvements and informing future research and development efforts.

3.6.5 Conclusion: Task 5 successfully delivered a functional Cloud-based Ride-sharing Application for the NC-CAV Testbed. This project created a complete software ecosystem. It includes a user mobile app, a driver interface, and a cloud backend. The system connects public users with our autonomous vehicles. We validated the platform through rigorous testing and field deployment. It demonstrated stable vehicle tracking, efficient ride scheduling, and robust data collection capabilities.

The project fulfilled its primary objective by establishing a dedicated operational backbone for the NC-CAV Testbed. This custom application is essential for the daily delivery of autonomous shuttle services. It acts as the central coordination point between our fleet and the public. By providing a direct interface, we ensure users are well-informed about schedules and real-time vehicle locations. Crucially, the system allows us to collect immediate feedback and identify specific user needs. This capability enables us to pinpoint areas for improvement. We now possess the necessary infrastructure to facilitate the service, coordinate operations, and use real-world data to guide the future of automated transportation.

3.6.6 Future Research Needs: Based on the deployment experience, several opportunities exist to further improve the service and expand the capabilities of the NC-CAV Testbed ride-sharing platform. Future work will focus on developing more advanced routing algorithms that move beyond the current queue-based matching approach to incorporate real-time traffic conditions and demand patterns, enabling faster and more efficient rides. Another important direction is integrating the application with local public transit systems, allowing users to plan multimodal trips that combine autonomous shuttles with existing bus services. Expanding the operational scope of the platform is also an important research area, including exploring use cases such as serving local businesses or supporting transportation during special events to evaluate different service models. Finally, improving user communication through features such as push notifications and real-time service alerts can enhance user experience by keeping passengers better informed about ride status, vehicle arrival times, and operational updates.

3.6.7 Relevance to NCDOT The development of this cloud-based ride-sharing platform directly supports NCDOT's mission to connect people and places safely and efficiently. By successfully deploying an autonomous shuttle service model. This platform is particularly relevant for serving rural communities where traditional fixed-route buses may be inefficient, offering a scalable solution to improve transit equity across the state.

Chapter 4 Outreach, Dissemination, and Workforce Development Activities under NC-CAV Center

4.1 Outreach and Workforce Development Activities under NC-CAV Center

The NC-CAV Center actively promotes outreach and workforce development to support education, research dissemination, and community engagement in connected and autonomous vehicle (CAV) technologies. Through seminars, workshops, student training, and public engagement activities, the center provides opportunities for students, researchers, industry partners, and the broader community to learn about emerging transportation technologies. These activities help build a skilled workforce, foster interdisciplinary collaboration, and increase public awareness of innovations in intelligent transportation systems. EXamples include:

1. **Title of The Activity/Event:** Demonstration of Remote Operation of Automated Shuttles at TRB 2026
    - **Description of the Activity/Event:** NC-CAV demonstrated remote operation of automated shuttles at the Transportation Research Board (TRB) 2026 Annual Meeting, showcasing research outcomes to transportation researchers, policymakers, and industry stakeholders.
    - **Date:** January 2026
    - **Link:** `https://www.nccav.com/news/2026-01-trb-remote-operation-demo`
2. **Title of The Activity/Event:** Jamestown Middle School STEM Scholars Campus Visit
    - **Description of the Activity/Event:** The center hosted 58 middle school STEM scholars for an immersive campus visit introducing students to connected and autonomous vehicle technologies and engineering careers.
    - **Date:** December 2025
    - **Link:** `https://www.nccav.com/news/2025-12-jamestown-middle-school-stem-visit`
3. **Title of The Activity/Event:** Summer Transportation Institute Facility Tour
    - **Description of the Activity/Event:** The NC-CAV Center partnered with the Transportation Institute to host Summer Transportation Institute students for demonstrations and facility tours.
    - **Date:** July 2025
    - **Link:** `https://www.nccav.com/news/2025-07-summer-transportation-institute`
4. **Title of The Activity/Event:** NCDOT Summer Internship Program Visit
    - **Description of the Activity/Event:** Twenty-five NCDOT summer interns visited the facility to learn about autonomous vehicle technologies and transportation research infrastructure.
    - **Date:** July 2025
    - **Link:** `https://www.nccav.com/news/2025-07-ncdot-intern-visit`
5. **Title of The Activity/Event:** Robotics and Coding Camp Student Outreach Visit
    - **Description of the Activity/Event:** Elementary students from a robotics and coding camp participated in a hands-on outreach visit exploring autonomous vehicle technologies.
    - **Date:** July 2025
    - **Link:** `https://www.nccav.com/news/2025-07-robotics-coding-camp`
6. **Title of The Activity/Event:** Pilot Elementary School STEM Outreach
    - **Description of the Activity/Event:** NC-CAV researchers introduced elementary students to engineering concepts through demonstrations of connected vehicle technologies.
    - **Date:** May 2025
    - **Link:** `https://www.nccav.com/news/2025-05-pilot-elementary-stem`

7. **Title of The Activity/Event:** Autonomous Vehicle Demonstration for Transportation Professionals
    - **Description of the Activity/Event:** Transportation professionals visited the facility for demonstrations of advanced autonomous vehicle systems and research projects.
    - **Date:** May 2025
    - **Link:** `https://www.nccav.com/news/2025-05-transportation-professionals-demo`
8. **Title of The Activity/Event:** NCDOT Leadership Visit to NC A&T Transportation Facilities
    - **Description of the Activity/Event:** North Carolina transportation leaders visited NC A&T research facilities to observe demonstrations of connected and autonomous vehicle technologies.
    - **Date:** April 2025
    - **Link:** `https://www.nccav.com/news/2025-04-ncdot-leadership-visit`
9. **Title of The Activity/Event:** NCDOT Roadshow Event
    - **Description of the Activity/Event:** The NC-CAV Center hosted an NCDOT roadshow event highlighting emerging transportation technologies and collaborative research activities.
    - **Date:** February 2025
    - **Link:** `https://www.nccav.com/news/2025-02-ncdot-roadshow`
10. **Title of The Activity/Event:** Winston-Salem Career Center Drone Technology Class Visit
    - **Description of the Activity/Event:** Students from a drone technology program toured NC-CAV research facilities to learn about autonomous transportation technologies.
    - **Date:** February 2025
    - **Link:** `https://www.nccav.com/news/2025-02-drone-class-visit`
11. **Title of The Activity/Event:** NC Advanced Mobility Symposium Facility Tour
    - **Description of the Activity/Event:** Participants of the NC Advanced Mobility Symposium attended an interactive tour of the unmanned aircraft systems and urban air mobility research facilities.
    - **Date:** November 2024
    - **Link:** `https://www.nccav.com/news/2024-11-advanced-mobility-symposium`
12. **Title of The Activity/Event:** Western Guilford High School Facility Tour
    - **Description of the Activity/Event:** High school seniors visited the NC-CAV Center for an immersive introduction to transportation engineering and autonomous vehicle research.
    - **Date:** November 2024
    - **Link:** `https://www.nccav.com/news/2024-11-western-guilford-tour`
13. **Title of The Activity/Event:** Troy's Honorary Intern Social (THIS) Program Visit
    - **Description of the Activity/Event:** The NC-CAV Center hosted interns from the Institute of Transportation Engineers THIS program for research demonstrations and networking.
    - **Date:** July 2024
    - **Link:** `https://www.nccav.com/news/2024-07-this-program`
14. **Title of The Activity/Event:** Summer High School Transportation Institute
    - **Description of the Activity/Event:** High school students from multiple states participated in hands-on learning activities focused on transportation engineering and emerging mobility technologies.
    - **Date:** July 2024

- **Link:** `https://www.nccav.com/news/2024-07-high-school-sti`

15. **Title of The Activity/Event:** U.S. Department of Transportation Leadership Visit
    - **Description of the Activity/Event:** U.S. Secretary of Transportation Pete Buttigieg and state leaders visited NC-CAV research facilities to observe demonstrations of rural autonomous vehicle research.
    - **Date:** July 2024
    - **Link:** `https://www.nccav.com/news/2024-07-usdot-visit`
16. **Title of The Activity/Event:** NC Transportation Summit Technology Day
    - **Description of the Activity/Event:** NC-CAV showcased advanced transportation technologies during a technology day preceding the North Carolina Transportation Summit.
    - **Date:** May 2024
    - **Link:** `https://www.nccav.com/news/2024-05-nc-transportation-summit`
17. **Title of The Activity/Event:** Piedmont Triad K-12 STEM Student Enrichment Event
    - **Description of the Activity/Event:** Autonomous vehicle technologies were demonstrated to K-12 students to inspire interest in STEM education and transportation innovation.
    - **Date:** April 2024
    - **Link:** `https://www.nccav.com/news/2024-04-k12-stem-event`
18. **Title of The Activity/Event:** Greensboro Leadership Visit to Rural AV Test Facility
    - **Description of the Activity/Event:** Greensboro city leadership toured the rural autonomous vehicle test facility to learn about research activities and collaboration opportunities.
    - **Date:** March 2024
    - **Link:** `https://www.nccav.com/news/2024-03-greensboro-visit`
19. **Title of The Activity/Event:** Engineers Week Outreach Activities
    - **Description of the Activity/Event:** The center engaged students during Engineers Week through demonstrations and educational outreach focused on engineering careers.
    - **Date:** February 2024
    - **Link:** `https://www.nccav.com/news/2024-02-engineers-week`
20. **Title of The Activity/Event:** Aggie Autonomous Shuttle Deployment
    - **Description of the Activity/Event:** The NC-CAV Center launched the Aggie Autonomous Shuttle service to demonstrate microtransit solutions connecting NC A&T and East Greensboro.
    - **Date:** September 2023
    - **Link:** `https://www.nccav.com/news/2023-09-aggie-autonomous-shuttle`

Chapter 5 Implementation and Technology Transfer Plan

5.1 Research Products

The following products represent the practical outcomes of the conducted research and are designed to support data-driven decision-making, technology evaluation, and strategic deployment planning within North Carolina's transportation system. These products include structured methodologies, validated simulation environments, optimization frameworks, and scalable control strategies that enable systematic assessment of operational performance, safety, efficiency, and emerging mobility technologies under realistic traffic conditions.

- **Product 1**
  - **Product Name:** Integrated CAV Work Zone Assessment Toolkit
  - **Product Description:** A comprehensive toolkit consisting of (1) a technical report on CAV impacts in work zones under mixed vehicle fleets, (2) structured simulation guidelines for evaluating emerging transportation technologies, and (3) a rigorous simulation model calibration framework to accurately replicate real-world traffic conditions. Together, these components support systematic assessment of operational and safety impacts associated with CAV integration in work zones.
  - **Suggested User:** NCDOT Traffic Mobility and Safety Division.
  - **Recommended Use:** Evaluation of operational and safety implications of CAV deployment and other emerging technologies in work zones using calibrated and methodologically sound simulation approaches.
  - **Recommended Training:** Basic to intermediate training in CAV technologies, mixed traffic operations, work zone management, traffic simulation, and model calibration concepts.
- **Product 2**
  - **Product Name:** Distributed Intelligent Ridesharing Optimization Framework (DIROF)
  - **Product Description:** An integrated, deployment-ready ridesharing optimization framework that combines (1) graph-based diffusion convolution demand prediction, (2) dynamic pricing with adaptive tipping strategies, and (3) a hybrid integrated routing engine (IRE) that merges OSRM and A* algorithms for real-time route computation. The framework utilizes a distributed Deep Q-Network (DQN) architecture to enable proactive vehicle dispatching, improved fleet utilization, and economically efficient operations under dynamic traffic conditions. Validated using large-scale real-world datasets, the framework demonstrated up to 20% improvement in vehicle profitability, 13% reduction in travel distance, 10% reduction in idle time, and significant reductions in passenger waiting time compared to baseline methods.
  - **Suggested User:** NCDOT Integrated Mobility Division, Public Transportation Division, and Emerging Mobility and Innovation Units.
  - **Recommended Use:** Evaluation, pilot deployment, and strategic planning of on-demand shared mobility systems, including CAV-enabled fleet operations, urban ridesharing programs, first/last-mile solutions, and integrated multimodal mobility services.
  - **Recommended Training:** Intermediate training in CAV-enabled mobility systems, reinforcement learning concepts, graph-based demand prediction models, dynamic pricing strategies, and intelligent routing algorithms.
- **Product 3**
  - **Product Name:** CAV Hardware in loop simulation
  - **Product Description:** The CAV hardware-in-the-loop (HiL) simulation provides a way to integrate a physical CAV testbed with software-based simulation, creating a hybrid platform in which real CAV data communication with an edge computing network can be tested. This allows researchers and transportation teams to study realistic driving, traffic, and communication scenarios in a safe and repeatable environment while still using actual hardware, helping them understand how the system will respond before deploying it on real roads. Details about the development and operation of this method will be delivered in a report.

  - **Suggested User:** CAV network operations and testing engineers
  - **Recommended Use:** Test methods for improving data communication between CAVs and edge infrastructure before deployment.
  - **Recommended Training:** SUMO software and python based programs.

- **Product 4**
  - **Product Name:** CAV digital twin software
  - **Product Description:** The CAV digital twin software is a virtual copy of a real driving environment built inside the CARLA simulator. It includes a virtual prototype of NCA&T's roundabout test track and python scripts to generate a digital object of CAV to test how connected and autonomous vehicles might behave on this road without using the real road every time. CARLA is an open-source platform made for developing and testing self-driving systems, and its digital twin tools can build realistic 3D environments from real map data such as OpenStreetMap/OpenDRIVE. The method to deploy the software and related components will be delivered using a Github repository.
  - **Suggested User:** CAV operations and testing engineers
  - **Recommended Use:** Test how connected and autonomous vehicles might behave on roundabout without using the real road.
  - **Recommended Training:** Operating CARLA simulator software and python based programs.

- **Product 5**
  - **Product Name:** Real-Time Cybersecurity Monitoring Framework for Connected Transportation Infrastructure
  - **Product Description: Product Description:** The Real-Time Cybersecurity Monitoring Framework for Connected Transportation Infrastructure is a validated reference architecture for distributed intrusion detection across connected vehicle and roadside environments. It defines an end-to-end monitoring approach in which participating transportation assets contribute to collaborative model improvement while maintaining local data control. The framework captures experimentally supported design choices for scalable anomaly detection under heterogeneous device capability and multi-site infrastructure conditions typical of connected transportation programs.

    The framework incorporates mechanisms intended to maintain detection stability when some participants are unreliable or compromised, and it characterizes practical trade-offs relevant to operational planning, including detection performance under adversarial participation, coordination overhead, and edge feasibility constraints. The product is intended to provide NCDOT with an evidence-based foundation to evaluate and mature cybersecurity monitoring capabilities for future deployment contexts such as connected corridors, roadside unit networks, and smart work zone environments.
  - **Suggested User:** North Carolina Department of Transportation cybersecurity personnel, connected vehicle program managers, transportation operations teams, and infrastructure technology planners.
  - **Recommended Use:** Apply this framework as a program planning and evaluation aid. Use it to (i) define cybersecurity monitoring requirements for connected transportation pilots, (ii) evaluate candidate intrusion detection approaches using consistent metrics and adversarial test conditions, and (iii) document evidence-based decisions when selecting monitoring architectures for corridor-scale expansion. The framework can also be used to structure internal technical reviews and to support vendor and system assessments by providing a common basis for performance and robustness evaluation.
  - **Recommended Training:** Familiarity with connected transportation system architectures, intrusion detection fundamentals, and cybersecurity incident response procedures is recommended. Technical personnel applying the framework should also understand distributed training coordination, basic performance evaluation metrics, and practical constraints associated with resource-limited field devices.

- **Product 6**
  - **Product Name:** Cooperative CAV Trajectory Control Framework for Roundabout

  - **Product Description:** A comprehensive framework that generates optimal CAV control decisions by utilizing V2V or V2I connectivity. The framework has been tested under various demand scenarios using a microscopic simulation model of a single-lane roundabout. The framework provides (a) a nonlinear trajectory optimization algorithm and (b) a heuristic-based control algorithm to generate safe, efficient, and real-time CAV coordination. The optimization-based framework builds the mathematical ground for real-world deployment with an aim to maximize operational benefits. On the other hand, the heuristics-based CAV control framework aims at achieving scalability and real-time implementability. Thus, the heuristics-based control serves as a deployable control framework where CAVs function as mobile traffic controllers and facilitates coordinated gap creation and communication-based merging assistance to circulating vehicles. Overall, the frameworks propose innovative methods to roundabout operation and enable systematic assessment of how effective utilization of CAVs can influence roundabout efficiency and capacity without requiring geometric redesign.
  - **Suggested User:** NCDOT Traffic Mobility and Safety Division; Transportation Planning Division; ITS and Connected Vehicle Program Units; NCDOT ITS Deployment Unit.
  - **Recommended Use:** Evaluation of operational improvements at existing and planned roundabouts, scenario testing for increasing traffic demand, and strategic planning for phased CAV integration into North Carolina's roundabout network. Pilot implementation planning, feasibility assessment of cooperative CAV control at roundabouts, and long-term modernization of unsignalized intersection operations without physical expansion.
  - **Recommended Training:** Intermediate and advanced training in CAV technologies, roundabout operations, microscopic traffic simulation (e.g., PTV VISSIM), trajectory optimization, and performance analysis metrics.

- **Product 4**
  - **Product Name:** Cooperative CAV Coordination and Communication Platform for Roundabout Operations
  - **Product Description:** A field-validated, scalable communication and coordination platform designed to support cooperative Connected and Automated Vehicle (CAV) operations in roundabout environments. The platform integrates ROS2-based onboard Automated Driving Systems (ADS), commercial 5G networking hardware, a centralized WebSocket-enabled server architecture, and a secure web-based control interface to enable real-time, bidirectional data exchange among multiple CAVs. The system aggregates GNSS position, velocity, and vehicle state information to a centralized coordination algorithm that computes and transmits dynamically regulated speed commands to approaching vehicles, thereby managing entry behavior and facilitating safe gap creation. Experimental validation conducted in a controlled roundabout test environment demonstrates reliable telemetry transmission, stable command execution, and effective coordination across vehicles. The platform provides an implementation-ready prototype and establishes the technical foundation for scalable cooperative CAV deployment at unsignalized intersections.
  - **Suggested User:** NCDOT Intelligent Transportation Systems (ITS) Unit; Connected and Automated Vehicle (CAV) Program Office; Traffic Operations and Congestion Management Units; and Transportation Systems Management and Operations (TSMO) Division.
  - **Recommended Use:** Pilot deployment planning, evaluation of connectivity-enabled roundabout control strategies, assessment of communication infrastructure requirements for CAV integration, and phased implementation of cooperative vehicle coordination frameworks within North Carolina's roadway network.
  - **Recommended Training:** Intermediate to advanced training in connected vehicle communication architectures (5G/V2X), ROS2-based vehicle integration, centralized traffic coordination algorithms, cybersecurity considerations for connected infrastructure, and real-time transportation systems operations.

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 thorughout 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:** Innovations in Transportation: CAVs, Generative AI, and the Future of Transit
   - **Speaker:** Dr. Raphael Stern, Dr. Michael Levin, Dr. Seongjin Choi, Dr. Alireza Khani
   - **Date:** April 25, 2025
   - **Link:** `https://www.nccav.com/seminars/2025-04-cr2c2-joint-seminar`
2. **Title:** Analyzing the Unseen: Modular Open-Source Geospatial Data Science Ecosystem
   - **Speaker:** Dr. Jinha Jung
   - **Date:** March 28, 2025
   - **Link:** `https://www.nccav.com/seminars/2025-03-jinha-jung`
3. **Title:** Using Connected Autonomous Vehicles as Mobile Traffic Controllers in Roundabouts
   - **Speaker:** Mr. Abdullah Al Farabi
   - **Date:** February 28, 2025
   - **Link:** `https://www.nccav.com/seminars/2025-02-abdullah-al-farabi`
4. **Title:** Transit Signal Priority Control with Connected Vehicle Technology: Deep Reinforcement Learning Approach
   - **Speaker:** Dr. Tianjia Yang
   - **Date:** January 31, 2025
   - **Link:** `https://www.nccav.com/seminars/2025-01-tianjia-yang`
5. **Title:** Federated Learning-based Intrusion Detection Systems in the Autonomous Vehicle Ecosystem
   - **Speaker:** Mr. Robert Akinie
   - **Date:** October 25, 2024
   - **Link:** `https://www.nccav.com/seminars/2024-10-robert-akinie`
6. **Title:** CAVs and Nighttime Mobility: Towards Equitable Transportation Systems
   - **Speaker:** Dr. Matthew Palm
   - **Date:** April 26, 2024
   - **Link:** `https://www.nccav.com/seminars/2024-04-matthew-palm`
7. **Title:** Regularized Stacked LSTM Car-Following Model for Autonomous Vehicles in Mixed Traffic
   - **Speaker:** Dr. Shoaib Samandar and Dr. Tanmay Das
   - **Date:** February 23, 2024
   - **Link:** `https://www.nccav.com/seminars/2024-02-samandar-das`
8. **Title:** An Efficient and Scalable Vehicle Dispatching Technique for Ridesharing
   - **Speaker:** Mr. Benjamin Lartey
   - **Date:** October 27, 2023
   - **Link:** `https://www.nccav.com/seminars/2023-10-benjamin-lartey`
9. **Title:** UAV-Assisted Bridge Inspection: Development and Testing of an End-to-End Operational Workflow
   - **Speaker:** Mr. Emmanuel Marfo
   - **Date:** September 29, 2023
   - **Link:** `https://www.nccav.com/seminars/2023-09-emmanuel-marfo`
10. **Title:** Transforming Traffic Monitoring with UAVs and AI-Based Vehicle Counting
    - **Speaker:** Mr. Tewodros Gebre

  - **Date:** April 28, 2023
  - **Link:** `https://www.nccav.com/seminars/2023-04-tewodros-gebre`

11. **Title:** Profit-Aware Large-Scale Vehicle Dispatch Framework for Ridesharing
    - **Speaker:** Mr. Benjamin Lartey
    - **Date:** March 31, 2023
    - **Link:** `https://www.nccav.com/seminars/2023-03-benjamin-lartey`
12. **Title:** Security and Resiliency of Cyber-Physical-Social Systems for Connected and Automated Transportation Systems
    - **Speaker:** Dr. Mashrur "Ronnie" Chowdhury
    - **Date:** January 28, 2022
    - **Link:** `https://www.nccav.com/seminars/2022-1-dr-mashrur-ronnie-chowdhury`
13. **Title:** Implementing Solutions from Transportation Research and Evaluating Emerging Technologies (I-STREET)
    - **Speaker:** Dr. Pruthvi Manjunatha
    - **Date:** November 29, 2021
    - **Link:** `https://www.nccav.com/seminars/2021-11-dr-pruthvi-manjunatha`
14. **Title:** Impact of Automated, Connected, Electric, and Shared Vehicles on Transportation Revenue Collection
    - **Speaker:** Dr. Steven Jiang
    - **Date:** September 24, 2021
    - **Link:** `https://www.nccav.com/seminars/2021-9-dr-steven-jiang`
15. **Title:** Mitigating Freeway Congestion at Bottlenecks through Variable Speed Limit Control in Connected Autonomous Vehicle Environment
    - **Speaker:** Dr. Wei Fan
    - **Date:** May 28, 2021
    - **Link:** `https://www.nccav.com/seminars/2021-5-wie-fan`
16. **Title:** Machine Learning-Enabled and Ultra-Low Latency Connected Transportation
    - **Speaker:** Dr. Shih-Chun Lin
    - **Date:** March 26, 2021
    - **Link:** `https://www.nccav.com/seminars/2021-3-shih-chun-lin`
17. **Title:** Introduction to Connected Traffic Signals
    - **Speaker:** Mr. Thomas Chase
    - **Date:** October 30, 2020
    - **Link:** `https://www.nccav.com/seminars/2020-10-thomas-chase`
18. **Title:** Anomaly Detection for Autonomous Driving
    - **Speaker:** Dr. Abdullah Al Redwan Newaz
    - **Date:** September 25, 2020
    - **Link:** `https://www.nccav.com/seminars/2020-9-redwannewaz`

5.2.2 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] Lartey, Benjamin, Wendwosen Bedada, Xuyang Yan, Abdollah Homaifar, Ali Karimoddini, and Edward Tunstel, "*An Efficient Profit-Aware Scalable Vehicle Dispatch Framework for On-Demand Ridesharing,*" IEEE Transactions on Industrial Cyber-Physical Systems (2024).

[4] Abdullah Al Farabi and Ali Hajbabaie, "*Using Connected and Automated Vehicles as Mobile Traffic Controllers in Single-Lane Roundabouts.,*" Under review.

[5] Abdullah Al Farabi and Ali Hajbabaie, "*Real-Time Trajectory Construction Heuristic for Connected Automated Vehicles in Single-lane Roundabouts.,*" Under review.

[6] Shahriar, M. S., Ahmed, F., Chen, G., Pham, K. D., Subramaniam, S., Matsuura, M., Hasegawa, H., and Lin, S. C. (2025, May). Multi-Tenant Traffic Prioritization and On-Demand QoS Provisioning in Digital Twin-Empowered Programmable Edge Networks. In NOMS 2025-2025 IEEE Network Operations and Management Symposium (pp. 1-6). IEEE.

[7] Shahriar, M. S., Subramaniam, S., Matsuura, M., Hasegawa, H., and Lin, S. C. (2024, October). Digital twin enabled data-driven approach for traffic efficiency and software-defined vehicular network optimization. In 2024 IEEE 100th Vehicular Technology Conference (VTC2024-Fall) (pp. 1-7). IEEE.

[8] Shahriar, M. S., Subramaniam, S., Matsuura, M., Hasegawa, H., and Lin, S. C. (2025). Intelligent edge resource provisioning for scalable digital twins of autonomous vehicles. Presented at 2025 IEEE Global Communications Conference (GLOBECOM), arXiv preprint arXiv:2508.11574.

[9] Akinie, Robert, Nana Kankam Gyimah, Mansi Bhavsar, and John Kelly, "*Fine-Tuning Federated Learning-Based Intrusion Detection Systems for Transportation IoT,*" In 2025 IEEE SoutheastCon, pages 1155-1161. IEEE, 2025.

Chapter 6 Conclusions

The NC Transportation Center of Excellence on Connected and Autonomous Vehicle Technology (NC-CAV) was established to support North Carolina's transition toward emerging intelligent transportation systems by conducting coordinated, multidisciplinary research on connected and automated vehicle (CAV) technologies. Through the collaboration of researchers at North Carolina A&T State University, North Carolina State University, and the University of North Carolina at Charlotte, the Center has developed a comprehensive research program addressing technical, operational, and societal aspects of automated transportation systems. Over the course of Phase 2, the Center expanded the knowledge base developed during the initial phase and further strengthened the research infrastructure necessary for studying advanced mobility technologies within the state. The collective efforts of the participating institutions demonstrate the value of collaborative research in addressing complex transportation challenges and supporting long-term strategic planning for the North Carolina Department of Transportation (NCDOT).

A major focus of the Center's work has been to improve understanding of how CAV technologies may influence roadway safety and traffic operations in environments that present elevated levels of complexity and risk. Among these environments, roadway work zones represent one of the most critical areas of study due to their temporary configurations, fluctuating traffic conditions, and historically higher crash rates. Through detailed simulation modeling and systematic evaluation of multiple traffic demand scenarios, the research conducted under this program examined how increasing levels of automated and connected vehicle participation could influence mobility and safety outcomes. The results provide important insights for transportation planners and engineers by illustrating potential improvements in traffic stability and operational efficiency as automation technologies become more prevalent. At the same time, the findings emphasize that transitional periods—during which both automated and human-driven vehicles share the roadway—will require careful planning, adaptive traffic management strategies, and continued research.

Another significant contribution of the Center involves the advancement of digital infrastructure concepts that enable reliable communication between vehicles and roadway systems. As connected mobility technologies continue to evolve, transportation agencies must prepare for a future in which infrastructure is increasingly integrated with computational and communication capabilities. The NC-CAV research program explored these requirements through the development of edge computing architectures and scalable test environments capable of evaluating connected vehicle technologies under controlled yet realistic conditions. The use of hardware-in-the-loop platforms and digital twin models allows researchers and transportation agencies to replicate real-world conditions within a controlled research setting. These capabilities provide a valuable tool for testing emerging transportation technologies, assessing infrastructure readiness, and identifying potential operational challenges prior to large-scale deployment.

The research also addressed the growing importance of cybersecurity within connected transportation systems. As vehicles, roadside infrastructure, and communication networks become increasingly interconnected, maintaining the security and reliability of these systems becomes a critical concern. The work conducted by the NC-CAV Center examined methods for identifying and mitigating cyber threats within connected vehicle environments, including the development of intrusion detection strategies and distributed learning approaches for improving system resilience. By incorporating cybersecurity considerations directly into the design and evaluation of connected infrastructure frameworks, the Center's research contributes to a more robust and trustworthy foundation for future transportation technologies.

Beyond infrastructure and safety analysis, the Center investigated how CAV technologies may enable new forms of transportation services and operational improvements. Several research activities focused on emerging mobility applications such as intelligent ride-sharing systems and cooperative vehicle control strategies designed to improve traffic flow through complex intersections and roundabouts. These efforts explored how real-time communication, advanced algorithms, and coordinated vehicle behavior can enhance the efficiency of transportation networks. Experimental testing and simulation studies conducted as part of this research demonstrated that such approaches have the potential to improve roadway capacity, reduce congestion, and enable more flexible mobility services in both urban and regional transportation systems.

The NC-CAV Center has also made meaningful contributions to the development of the future transportation workforce. Through the involvement of graduate and undergraduate students in multidisciplinary research activities, the program has provided valuable training opportunities in areas such as autonomous vehicle systems, intelligent transportation infrastructure, cybersecurity, and data analytics. These experiences not only enhance students' technical skills but also prepare them to address the evolving challenges associated with next-generation mobility systems. In addition to student training, the Center has supported outreach, dissemination, and collaboration activities that promote the exchange of knowledge among academic researchers, government agencies, and industry partners.

For NCDOT, the outcomes of this research initiative provide practical guidance and analytical tools that can inform strategic planning and infrastructure development efforts. The models, experimental platforms, and technology frameworks developed through the Center offer new capabilities for evaluating transportation innovations and assessing their potential impacts before implementation. These resources can assist NCDOT in developing proactive policies and investment strategies that support the gradual integration of automated and connected vehicle technologies across the state's transportation network. In addition, the research findings contribute to a broader understanding of how emerging mobility technologies may influence traffic operations, roadway design, and transportation system management in the coming decades.

The broader significance of the NC-CAV Center extends beyond the state of North Carolina. By integrating expertise from multiple engineering disciplines—including transportation engineering, computer science, communications systems, and control theory—the Center provides a model for how universities and public agencies can collaborate to address the technical and policy challenges associated with automated mobility. The methodologies, experimental platforms, and analytical approaches developed through this program can inform similar research efforts nationwide and contribute to the advancement of intelligent transportation systems at the national level.

Overall, Phase 2 of the NC-CAV Center has demonstrated the importance of sustained research investment in emerging transportation technologies. The program has produced new knowledge, experimental tools, and implementation insights that will support both near-term and long-term transportation planning efforts. By strengthening the research ecosystem surrounding connected and automated vehicle technologies, the Center has positioned North Carolina to remain at the forefront of innovation in transportation systems. Continued collaboration between academic institutions, transportation agencies, and industry partners will be essential to ensure that the benefits of these technologies—including improved safety, enhanced mobility, and more efficient transportation networks—are realized in a manner that serves the needs of communities throughout the state and beyond.

APPENDIX: A
Appendix A: Detailed Analysis of the Impact of Connected and Automated Vehicles on Work Zones

Appendix A Detailed Analysis of the Impact of Connected and Automated Vehicles on Work Zones

A.1 Background

A.1.1 Problem Statement and Motivation Connected and Autonomous Vehicles (CAVs) have emerged as a transformative technology in the transportation industry, offering the promise of improved safety, reduced congestion, and enhanced efficiency [85]. Equipped with advanced sensors, communication capabilities, and automated driving functions, CAVs have the potential to revolutionize the way people and goods move across modern transportation networks. As CAV technology continues to advance, its gradual integration into real-world traffic environments has become increasingly inevitable. At the same time, work zones have become more frequent on highways due to the growing demand for roadway maintenance, construction, and infrastructure improvements [96]. These work zone segments often introduce sudden geometric changes, lane reductions, and complex traffic control schemes that disrupt normal driving patterns. Such disruptions not only reduce roadway capacity and cause congestion [35] but also pose significant safety risks for both drivers and construction workers [192]. The Federal Highway Administration (FHWA) estimates that work zones account for roughly 10% of total road delay in the United States, behind recurring bottlenecks (40%), traffic crashes (25%), and inclement weather (14%) [45]. In North Carolina, the work zone crash data recorded 29 fatalities and over 2,500 injuries among more than 6,200 work zone crashes in 2021 [113]. Given these trends, the future transportation system will involve unavoidable interaction between CAVs and work zones. While CAVs have shown promising capabilities in managing complex driving scenarios, including shorter headways, faster reaction times, and eliminating human error leading to crashes [36], their behavior and performance in the highly variable and constrained environment of work zones remain largely underexplored. Current methods for evaluating work zone performance and safety do not fully account for the influence of CAVs, particularly under mixed traffic conditions where human-driven vehicles and CAVs will coexist for an extended period. This research aims to investigate the effects of CAVs on safety, mobility, and environmental sustainability. The study will examine how different levels of CAVs market penetration influence crash risk, traffic flow, and metrics related to environmental performance in work zones. It will also identify strategies to optimize the integration of CAVs into these challenging environments. The results will provide valuable insights for transportation practitioners and will contribute to the development of guidelines and best practices for managing the coexistence of CAVs and work zones in the near future.

A.1.2 Research Goals and Objectives The main goals of this research project investigate the impacts of CAVs on work zones and to identify strategies for integrating CAVs into work zones to enhance safety and efficiency. The objectives of this project are to:

- **Objective 1:** Conduct a comprehensive review of existing literature related to CAVs and work zones in order to identify gaps in knowledge and inform the research design.
- **Objective 2:** Identify and design work zones from real-world highways as potential scenarios.
- **Objective 3:** Create a simulation model to analyze the impacts of CAVs on work zones under different scenarios. The simulation model will consider variables such as work zone configurations, traffic volume, and CAV penetration rates.
- **Objective 4:** Develop a case study of a successful implementation of CAVs in a work zone to identify best practices and strategies for integrating CAVs into work zones.
- **Objective 5:** Conduct in-depth analysis and integrate results from this project, including refining insightful findings and providing recommendations for future research directions.

A.1.3 Expected Contributions The primary goal of this research is to assess the impacts of CAVs on work zone safety, mobility and environmental sustainability, through a comprehensive analysis of various work zone configurations under differing traffic demand levels and market penetration rates of AVs and CAVs. The parameter calibration process and results can guide engineers in evaluating the impact of cutting-edge technologies by applying simulation software and accurately reproducing real-world traffic conditions. The evaluation results of this study could provide a theoretical foundation for researchers to investigate the impact of CAVs on real-world work zones. The anticipated research contributions are expected to provide valuable insights for transportation practitioners and researchers by elucidating the relationship between work zone configurations and CAVs across varying traffic volumes and market penetration rates. The anticipated research products include:

- A technical report that documents the detailed review and potential benefits of CAV technologies and their impact on work zone considering mixed vehicle fleets with different expected levels of CAV market penetration.
- Guidelines for engineers to systematically apply simulation software to evaluate the impact of cutting-edge technologies.
- A rigorous parameter calibration framework developed for simulation models to accurately reproduce real-world traffic conditions.

A.2 Literature Review

A.2.1 Introduction

This chapter presents a comprehensive review of current research and practices related to Connected and Autonomous Vehicles (CAVs) and their potential impacts on work zones. The review begins by examining studies that address Autonomous Vehicles (AVs) and Connected Vehicles (CVs) individually, followed by research that considers the integrated effects of CAVs. It also includes a review of key studies focused on work zone operations and safety. The chapter concludes by summarizing findings from prior literature that explored the interaction between CVs, AVs, or CAVs and work zone environments.

A.2.2 Connected Vehicle & Autonomous Vehicle Technology

A.2.2.1 Connected Vehicles A Connected Vehicle (CV) is a vehicle that is equipped with communication technologies, allowing it to exchange information with other vehicles (Vehicle-to-Vehicle or V2V communication), infrastructure (Vehicle-to-Infrastructure or V2I communication), and even with cloud-based platforms [204]. CVs are characterized by their ability to share data related to their speed, location, direction, and more, with other vehicles and infrastructure elements. Key characteristics of CVs include:

- **Communication Systems:** As previously discussed by [204], CVs rely on specific communication systems that distinguish them from traditional Intelligent Transportation Systems (ITS). These wireless communication technologies, such as Dedicated Short-Range Communications (DSRC), cellular communications, Bluetooth, and satellite communications, play vital roles in facilitating data exchange for CVs. DSRC, operating in the 5.9 GHz spectrum, offers low-latency communication with a shorter range, suitable for applications like emergency warnings and adaptive cruise control. Cellular communications are ideal for non-time-critical purposes, despite their higher latency, with ongoing advancements potentially expanding their capabilities. Bluetooth communication provides varying ranges and higher latency, making it suitable for stationary tasks like map updates. Satellite communications, while offering extensive coverage, bluetooth communication have limitations in data capacity and high latency, making them less suitable for safety-critical applications. These wireless technologies collectively underpin the communication systems essential for improving situational awareness and safety in CVs.
- **Data Exchange:** Vehicle-to-vehicle (V2V) communication serves as a pivotal means for data exchange among connected vehicles. This innovative technology facilitates the wireless transmission of essential information encompassing the current status of vehicles, their intended maneuvers, and the prevalent environmental conditions [209]. Within this data stream, crucial warnings can emerge, alerting drivers to a spectrum of potential road hazards, including obstacles, traffic incidents, or adverse weather conditions. Moreover, V2V communication empowers CVs to navigate through traffic congestion more efficiently by sharing real-time traffic flow information. Additionally, the technology facilitates anticipatory responses to upcoming traffic signals, optimizing the flow of vehicles and reducing the risk of collisions [117].
- **Safety Benefits:** Primarily from a safety perspective, CVs offer remarkable benefits by providing drivers with instantaneous access to pertinent information regarding potential risks [140]. Whether due to the abrupt deceleration of a leading vehicle or a connected vehicle broadcasting an imminent lane change intention, CVs can process and relay this information to the driver, allowing them to take timely and informed actions. Such advanced features have the potential to mitigate crashes and enhance road safety significantly. Ultimately, CVs usher in a new era of vehicular communication, offering drivers a wealth of tools to anticipate and address

potential crashes. The technology holds the promise of significantly reducing the annual toll of traffic crashes, which in 2019 alone encompassed 6.8 million police-reported crashes, resulting in 36,096 fatalities and an estimated 2.7 million injuries [117].

A.2.2.2 Autonomous Vehicles An Autonomous Vehicle (AV) is a type of vehicle that is capable of operating without direct human input for various aspects of driving. The National Highway Traffic Safety Administration (NHTSA) defines AVs as vehicles that operates without direct driver input for steering, acceleration, and braking. These vehicles are designed to allow the driver not to constantly monitor the road while in self-driving mode [176]. The categorization and advancement of AVs have evolved over time, marked by the proposals of different taxonomies by various organizations. This diverse classification landscape serves as a testament to the dynamic nature of AV technology.

- **Autonomation Levels:** In the context of vehicle automation classification, the National Highway Traffic Safety Administration (NHTSA) marked a significant milestone in 2013 by introducing a four-level classification system for vehicle automation [42]. Following closely, in 2014, the Society of Automotive Engineers International (SAE) presented a more comprehensive six-level taxonomy [139]. Recognizing the merit of this expanded framework, NHTSA formally embraced the six-level classification system in 2016, firmly establishing it as the industry-standard reference for general application [42]. These six levels of vehicle automation, spanning from Level 0 through Level 5, delineate the spectrum of autonomous capabilities. Commencing at Level 0, the human driver exclusively operates the vehicle with no automation in play. Advancing to Levels 1 and 2, the driver retains responsibility for dynamic driving tasks (DDT), albeit with intermittent assistance from integrated advanced driver assistance systems (ADAS), which can provide support in steering, braking, and acceleration. ADAS exhibit potential in mitigating crashes by addressing driver errors to varying degrees. As we ascend to higher tiers of automation, the automated driving system (ADS) assumes complete control of the DDT upon activation. Level 3 introduces the concept of a fallback-ready user, prepared for DDT intervention when necessary. In contrast, Levels 4 and 5 usher in full autonomy, rendering the DDT fallback-ready user unnecessary, while Level 5 boasts an unrestricted operational design domain (ODD), distinguishing it from Levels 3 and 4. It is expected that within its ODD, an ADS eliminates driver errors, although disengagement from ADS, notably in Level 3 of automation, can pose intricate challenges [139].

- **Sensing and Perception:** AVs employ an array of sensors, including cameras, LiDAR, radar, and ultrasonic sensors, to comprehensively perceive their surroundings, capturing data about the vehicle's environment, neighboring vehicles, pedestrians, road signs [143, 200–202], and lane markings [48–52, 177].

- **Safety Systems:** Ensuring the safety of AVs is of paramount importance. AVs are equipped with advanced safety systems, including redundant hardware such as multiple sensors and backup steering and braking systems to ensure safe operation, even in the presence of hardware failures [10]. These safety systems extend beyond protecting vehicle occupants, incorporating features like adaptive cruise control and collision avoidance systems to safely interact with human-driven vehicles on the road [151, 195]. Compliance with evolving regulatory standards is another crucial aspect of AV safety, ensuring that AVs meet rigorous safety benchmarks before deployment on public roads [116]. This comprehensive, multidisciplinary approach is essential for advancing AV safety and building public trust in this transformative technology.

A.2.2.3 Connected and Autonomous Vehicles Connected and Autonomous Vehicles (CAVs) are vehicles that combine both autonomous driving capabilities and connectivity features. CAVs represent the convergence of AV and CV technologies, offering a holistic approach to transportation innovation. These vehicles are characterized by:

- **Automation and Connectivity:**CAVs are equipped with advanced technologies allowing these vehicles to operate at various levels of automation. Beyond their autonomous capabilities, they possess the remarkable ability to seamlessly communicate with other vehicles, infrastructure, and diverse systems, as highlighted by terminologies such as V2V (Vehicle-to-Vehicle), V2I (Vehicle-to-Infrastructure), and V2C (Vehicle-to-Cloud) [150]. This integration allows CAVs to make more informed decisions by considering data from both onboard sensors and external sources.

- **Enhanced Safety and Efficiency:** CAVs leverage sophisticated connectivity features to improve road safety and streamline traffic efficiency by eliminating the variability in driver's reaction to the received information (such as those from CV technology) [77, 87, 149]. Given the advancements in CAV technology and its potential to significantly reshape traffic flow and safety, it is crucial to understand how their integrated systems and sensors interpret and respond to diverse traffic scenarios, thereby promoting safer and more efficient transportation environments [26]. Besides, they can anticipate and react to changing traffic conditions in real-time, reducing the likelihood of crashes and traffic congestion.

- **Future Mobility Ecosystem:** While CAVs are increasingly recognized as a pivotal component of future mobility ecosystems, their societal implications, ranging from safety, to privacy and data security, have raised diverse concerns among different demographic groups, as evidenced by a comprehensive study conducted in the United States (Wali et al., 2021). It could potentially support concepts like autonomous ride-sharing [40], and smart city initiatives [174].

A.2.3 Potential Benefits of CAVs

A.2.3.1 Safety

- **Reduction in Human Error:**One of the most significant safety benefits of CAVs is the reduction in crashes caused by human error [13]. Studies have shown that over 90% of crashes are attributable to human mistakes, such as distracted driving, impaired driving, and failure to obey traffic rules [114]. CAVs are designed to operate with precision, follow traffic laws consistently, and react swiftly to potential hazards.
- **Advanced Driver Assistance Systems (ADAS):** CAVs are equipped with sophisticated Advanced Driver Assistance Systems, including adaptive cruise control, lane-keeping assist, and collision avoidance systems [88, 157]. These technologies enhance safety by assisting drivers in avoiding collisions, maintaining safe following distances, and staying within their lanes [194].
- **Predictive and Reactive Safety:** CAVs utilize sensor data, real-time communication with other vehicles and infrastructure, and advanced algorithms to predict and react to potential traffic incidents [166]. For example, they can detect an impending collision and take evasive action faster than a human driver.
- **Vulnerable Road User Protection:** CAVs are equipped with sensors that can detect pedestrians, cyclists, and other vulnerable road users [214]. This capability reduces the risk of crashes involving these road users.

A.2.3.2 Mobility

- **Improved Traffic Flow:** V2V will allow CAVs to orchestrate coordinated driving behaviors like merging and lane changes. As outlined by [30, 212], such synchronized operations translate to more seamless and predictable traffic flow. By mitigating sporadic braking and acceleration, which are primary contributors to traffic bottlenecks and carbon emissions [89], this inter-vehicle dialogue promises a transformative approach to alleviating traffic congestion and ensuring fluidity on our road.
- **Optimized Routing:** With V2I, CAVs can seamlessly access and analyze real-time traffic data [208]. This empowers them to intelligently choose the most optimal routes, ensuring quicker and more efficient journeys to their designated destinations [107]. This reduces congestion on heavily traveled routes and distributes traffic more evenly across road networks.
- **Increased Road Capacity:** CAVs can safely drive with shorter following distances and headways [21], increasing the capacity of existing roads and highways. This expansion of road capacity can accommodate growing traffic demands [53, 89].
- **Access to Emerging Mobility Services:** Within the evolving landscape of urban transport, CAVs are anticipated to seamlessly integrate into mobility-as-a-service (MaaS) platforms [147]. These integrations aim to offer residents streamlined, efficient, and tailored transit alternatives [189]. By harnessing the convenience of on-demand CAV services through such platforms, it is expected that there will be a significant shift away from the traditional paradigm of personal vehicle ownership, fostering a more sustainable and efficient urban mobility framework.
- **Equitable Mobility Access:** CAVs stand at the forefront of pioneering enhanced transportation accessibility, particularly for historically underserved communities that grapple with limited mobility choices. As highlighted by [68], these advancements extend beyond broader community benefits, offering solutions that greatly enhance mobility opportunities for individuals with disabilities and the elderly [60]. Such technological strides promise a more inclusive future, where mobility is not a privilege but an accessible right for all.

A.2.3.3 Environmental Impact

- **Fuel Efficiency:** CAVs harness cutting-edge technology to refine driving patterns, substantially curbing idling and tempering aggressive driving tendencies. Such enhancements pave the way for heightened fuel efficiency and notably diminished emissions [182]. Furthermore, their advanced navigation systems are adept at selecting routes that prioritize energy efficiency [19]. These collective advancements hint at a future where CAVs play a central role in promoting eco-friendly urban transit.

- **Synergy with Electrification:** CAVs complement electric vehicles by optimizing charging patterns, extending battery range, and improving fleet utilization. Automated electric taxis have been shown to reduce per-mile GHG emissions by over 90% [54], while shared electric fleets cut energy use by over 50% [20].

- **Reduced Parking Demand:** CAVs have the capability to autonomously drop off passengers and subsequently park in compact spaces [41, 184, 191]. Such efficiency not only diminishes the demand for expansive parking lots, but also reclaim urban space and lower land-use emissions.

- **Societal Rebound Effects :** Despite vehicle-level efficiency, CAVs may induce travel through increased accessibility and convenience. Newly mobile populations could contribute to a 14% rise in national VMT [60], while unoccupied travel in private CAVs may further elevate emissions if not properly managed.

A.2.4 Work Zones

A.2.4.1 Definition A work zone, as defined in the Highway Capacity Manual (HCM), is a delineated section of roadway where the critical activities of construction and maintenance intersect with the customary course of traffic. In this demarcated zone, one may observe alterations to the typical number of available lanes for vehicular movement or notable adjustments to the accustomed traffic flow dynamic [96, 169]. It is worth noting that work zones represent dynamic crucibles where the evolution and upkeep of transportation networks come into direct contact with the exigencies of real-time traffic management. As outlined in the Manual on Uniform Traffic Control Devices (MUTCD), work zones constitute a segment of a roadway where construction, maintenance, or utility work operations are in progress. Such a zone is commonly demarcated by signage, channeling equipment, barriers, road markings, and/or specialized work vehicles. Its span encompasses the area from the initial warning sign or the activation of high-intensity rotating, flashing, oscillating, or strobe lights on a vehicle to the point marked by the "END ROAD WORK" sign or the final temporary traffic control device [44].

A.2.4.2 Work Zone Sections A standard work zone consists of five main sections: the advanced warning area, the transition area, the buffer area, the activity or main event area, and the termination area [192]. In this section, a comprehensive definition of the various segments comprising a standard work zone is presented, drawing from the guidelines outlined by the MUTCD [109].

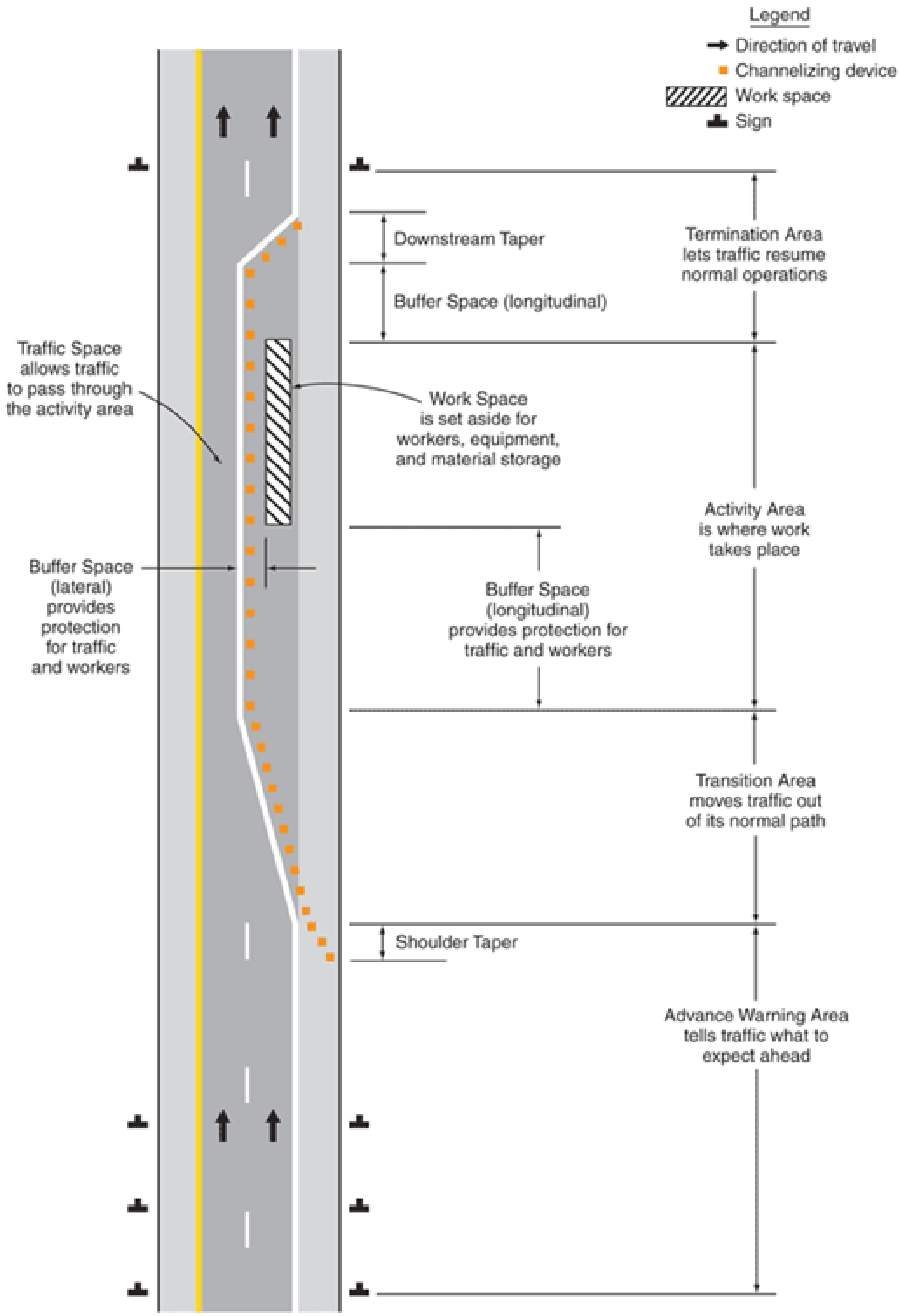


Figure 35. Component Parts of a Temporary Traffic Control Zone [109]

- **Advanced Warning Area:** In the initial phase, drivers are alerted to upcoming road closures, incidents, or lane changes through an advanced warning area. This alert can be conveyed through signage or identifying features such as strobe lights mounted on traffic vehicles. On high-speed roads, a series of advanced warning signs are often strategically placed to provide drivers with ample notice of an active temporary traffic control area ahead, thereby improving driver's compliance.

- **Transition Area:** The transition area is where drivers deviate from their regular travel path to navigate an alternate route. It involves establishing a new traffic channel or lane to facilitate a seamless transition from the standard route to the new one. If the work area shifts location, the transition area should relocate accordingly. The key feature of a transition area is a well-planned taper, the positioning of which is crucial for safeguarding worker safety. An appropriately positioned taper allows drivers sufficient time and distance to adjust their path to navigate the temporary lanes and maneuver around the work site.

- **The Buffer Area:** : A buffer area is designated without any materials, equipment, or storage of any kind. Typically aligned longitudinally or laterally along the direction of traffic flow, this buffer area sometimes serves to separate traffic from opposing directions within the work zone. Visual separation is often achieved with channelizing devices, creating a clearly defined buffer area.

- **Work/Activity Area:** While the term "work area" may lack a precise definition, it broadly encompasses any section of the highway where activities such as maintenance, construction, accident clearance, or utility work are conducted. The work zone should exhibit clear marking through appropriate signage, with channelizing devices forming a barricade between workers and the flow of traffic.it is also the most dangerous section in a work zone, statistically with roughly 66% of crashes occurring in the activity area [46].

- **Termination Area:** The termination area marks the point where both vehicular and pedestrian traffic return to their regular travel path. Located downstream of any work areas, it begins at the last temporary traffic control device. To signal the resumption of normal road operations, signage, such as a Speed Limit sign, may indicate a return to the standard speed limit.

A.2.4.3 Impacts of Work Zones

- **Crash rate:** The crash rate is a commonly employed metric for assessing the influence of work zones on safety. It is determined by dividing the total number of crashes that occurred during a specified timeframe by the vehicle miles traveled within the work zone segment [74]. Several researchers have done extensive research in work zone data analytics, particularly focusing on crash rates as a key indicator of safety within work zones. Crash rate have been employed to assess work zone safety. According to [192] a lot of studies have reported significant increases in crash rates during work zone presence. Factors contributing to this variability include work zone types, traffic conditions, and the quality of data used for calculations.

  Crash Type: Based on a comprehensive analysis of past literature and work zone data, it is evident that rear-end collisions are the most frequently occurring type of crashes within work zones [69, 74]. Sideswipe and angle collisions are also very frequent. According to the analyzed data from HSIS 15 years of crash data in North Carolina, when considering the severity of these incidents, rear-end collisions often emerge as more severe, underscoring the significance of rear-end collision prevention measures in work zone safety strategies.

- **Temporal Factors:** : The impact of work zone timing and duration on crash occurrences is complex and multifaceted. Nighttime construction has been associated with a significantly higher risk of fatal accidents [12], possibly due to reduced visibility. In contrast, most work zone crashes occur in clear daylight conditions, which can be attributed to increased traffic volume during these periods [136]. Daytime off-peak hours also present heightened risks for injury-related crashes [17].

- **Congestion Impact:**Work zones significantly influence traffic congestion [35], leading to increased travel times and decreased road capacity. Due to high demand, work zone-related congestion can extend the duration of peak traffic periods, exacerbating rush hour delays. Furthermore, congestion in work zones can result in inconsistent traffic speeds, which increase the likelihood of accidents, which could result in bottlenecks, thereby further exacerbating the traffic network condition.

- **Environmental Considerations:** according to [207] Work zones can have a notable environmental impact, primarily through increased emissions due to idling vehicles in congested areas . Prolonged construction activities can lead to higher fuel consumption and emission of pollutants, contributing to air quality related problems. Addressing these environmental challenges requires integrating sustainable practices in work zone planning, such as optimizing traffic flow with technology to reduce idling and incorporating eco-friendly road construction and maintenance practices.

A.2.5 CV/AV Technology in Work Zone Environment A substantial body of research has examined the application of Connected Vehicle (CV), Autonomous Vehicle (AV), and integrated Connected and Autonomous Vehicle (CAV) technologies within work zone environments. Existing studies primarily evaluate advisory systems, cooperative merging strategies, dynamic routing, speed harmonization, and platooning under varying traffic conditions and market penetration rates. Using methodologies such as microsimulation, agent-based modeling, driving simulator experiments, and reinforcement learning–based control, prior work generally reports improvements in mobility performance metrics, including reduced delay and queue length, as well as enhanced safety indicators such as conflict reduction and improved compliance.

Despite these promising findings, the effectiveness of CAV technologies in work zones is consistently shown to depend on traffic demand, behavioral assumptions, and penetration rates. Many studies rely on simulation-based frameworks and often assume idealized connectivity or high automation levels, leaving open questions regarding mixed traffic environments and practical deployment conditions. The table below summarizes the key objectives, methodologies, and findings of the most relevant studies in this area.

Table 8. Summary of Literature on CAVs in Work Zones

Study	**Objective**	**Methodology**	**Data Source**	**Key Findings**
Olia et al. (2012) [122]	Address congestion from infrastructure projects using CV systems	Microscopic simulation modeling traffic dynamics and CV system impacts	Modeled O-D matrix using gravity model (based on free-flow travel time)	CV systems reduce congestion and improve mobility and safety
Qiao et al. (2014) [131]	Explore RFID-based Driver Smart Assistance System for work zone safety	Field tests with 20 drivers using RFID communication	Human subject experiment	System improves driver compliance and reduces emissions, enhancing safety
Genders and Razavi Saiedeh (2016) [47]	Assess impact of CAVs on work zones with a dynamic route guidance system	Simulation using Paramics with V2V communication; Conservative, Moderate, Liberal driver models	Simulation traffic data	Higher Market Penetration Rate (40%) may reduce safety due to prioritizing time savings over distance
Ramadan (2016) [134]	Evaluate merge control strategies for long-duration work zones	Microsimulation for peak and off-peak traffic conditions	Empirical traffic data (GPS speeds, manual volume counts)	Merge strategies improve mobility and safety, challenging preference for off-peak scheduling
Zou and Qu (2018 [215]	Assess impact of CAVs on freeway work zone traffic operations	Cellular automata model simulating collaborative CAV behavior	Simulation traffic data	CAVs improve travel time, safety, and emissions, reducing operational variability
Abdulsattar et al. (2018) [3]	Assess safety impacts of CV technologies with different penetration rates and traffic conditions	Agent-Based Modeling and Simulation (ABMS) framework	Simulation traffic data	Higher CV penetration needed to achieve safety benefits, especially under high traffic
Abdulsattar et al. (2020) [2]	Evaluate mobility benefits of CVs in work zones on a two-lane highway	Agent-based modeling for V2V and V2I communication, varying traffic flow scenarios	Simulation traffic data	Mobility benefits linked to higher CV penetration, especially under high traffic
Raddaoui et al. (2020) [133]	Improve safety for large trucks in work zones using CV technology	Driving simulator experiment with 20 truck drivers under adverse weather conditions	Human subject experiment	CV-based warnings improve safety but multiple notifications can distract drivers
Ren et al. (2020) [137]	Enhance work zone safety and capacity using AI-based merge control	Cooperative driving model using reinforcement learning (SAC) in a fully automated environment	Simulation traffic data	AI-based merge control improves safety and mobility compared to traditional strategies
Wu et al. (2020) [188]	Evaluate CAV-based speed and lane-changing strategies in expressway work zones	Model predictive control for optimizing speed and lane-changing strategies	Simulation traffic data	Best strategies depend on traffic conditions; ELC+VSL best in heavy traffic with high CAV penetration
Mao et al. (2021) [97]	Compare safety of traditional DMS vs in-vehicle work zone warnings	Microsimulation comparing DMS and CV advisory systems	Simulation traffic data	CV warnings outperform DMS; optimal DMS placement depends on traffic conditions
Algomaiah and Li (2021) [6]	Analyze late merge strategies with and without CV technology	Microsimulation assessing throughput, delay, queue length and control variables	Simulation traffic data	CV-enabled late merge outperforms non-CV late merge, especially under moderate demand
Haque et al. (2023) [59]	Assess impact of platoons of connected heavy vehicles in work zones	Microsimulation calibrated to real work zone data	Empirical speed, volume, headway, and travel time data (Nebraska I-80 detectors + RITIS)	Increasing CAHV penetration improves safety and mobility in freeway work zones

A.3 Case Study

A.3.1 Introduction Building upon the literature review from the previous section, this chapter aims to identify potential freeway work zone segments and gather the necessary data for these segments. Due to the unavailability of freeway traffic flow data in North Carolina at the time of writing, we will utilize the California Department of Transportation (Caltrans) Performance Measurement System (PeMS) database to identify a potential freeway segment. A work zone will then be designed within this segment considering multiple configurations.

The structure of the following sections is as follows: Section A.3.2 provides an overview of the Caltrans Performance Measurement System (PeMS). Section A.3.3 outlines selected freeway segments and their associated data. Finally, Section A.3.4 summarizes the key findings and conclusions of this chapter.

A.3.2 The Caltrans Performance Measurement System The California Department of Transportation (Caltrans) Performance Measurement System (PeMS) provides essential access to both real-time and historical performance data in various formats and presentation styles. It serves as a crucial tool for managers, engineers, planners, and researchers to comprehend transportation performance, identify issues, and devise effective solutions. PeMS enables a comprehensive assessment of freeway performance, facilitating informed operational decisions based on current network conditions. It analyzes congestion bottlenecks to recommend potential remedies and supports overall improved decision-making processes. The key features of PeMS can be summarized as follows:

- **Data Collection and Integration:** PeMS serves as the centralized repository for all of Caltrans' real-time traffic data, consolidating information from over 44,681 detectors reporting data every 30 seconds. It integrates data from Intelligent Transportation System (ITS) Vehicle Detector Stations (VDS), traffic counters, weight-in-motion (WIM) sensors, and other sources across California's state highways.

- **Analytical Capabilities:** As a real-time Archive Data Management System (rt-ADMS), PeMS collects, stores, and processes raw data to generate insights. It offers built-in analytical tools for computing standard transportation performance measures such as vehicle miles traveled (VMT), vehicle hours traveled (VHT), delay (in vehicle-hours), and level of service (LOS). These capabilities support various traffic analyses, including Highway Capacity Manual assessments, Synchro analyses, and simulations.

- **Data Accessibility and Use:** Users can query both current and archived freeway traffic data, generate summary reports on freeway conditions, and compute specialized performance measures like travel time reliability indices.

- **Support for Transportation Planning:** PeMS data is instrumental in completing Project Study Reports and other transportation planning documents, aiding in model calibration, verifying study findings, and assessing traffic conditions for operational and capital improvements.

A.3.3 Identifying Potential Work Zones The area of interest is a particular segment of the I-5 freeway located in San Diego. This segment was selected for its strategic characteristics, including its minimal exposure to ramp-related traffic impacts, which ensures an environment conducive to studying freeway flow dynamics with minimal interruptions. This segment covers a total distance of about one mile (1.6 km), centered around postmile 26.64 as seen in Figure 36, and consists of a two-way interstate road with four lanes in each direction, each lane measuring 12 feet in width. The mainline speed limit for this section is set at 70 mph, other details regarding this freeway are presented in Table 9.

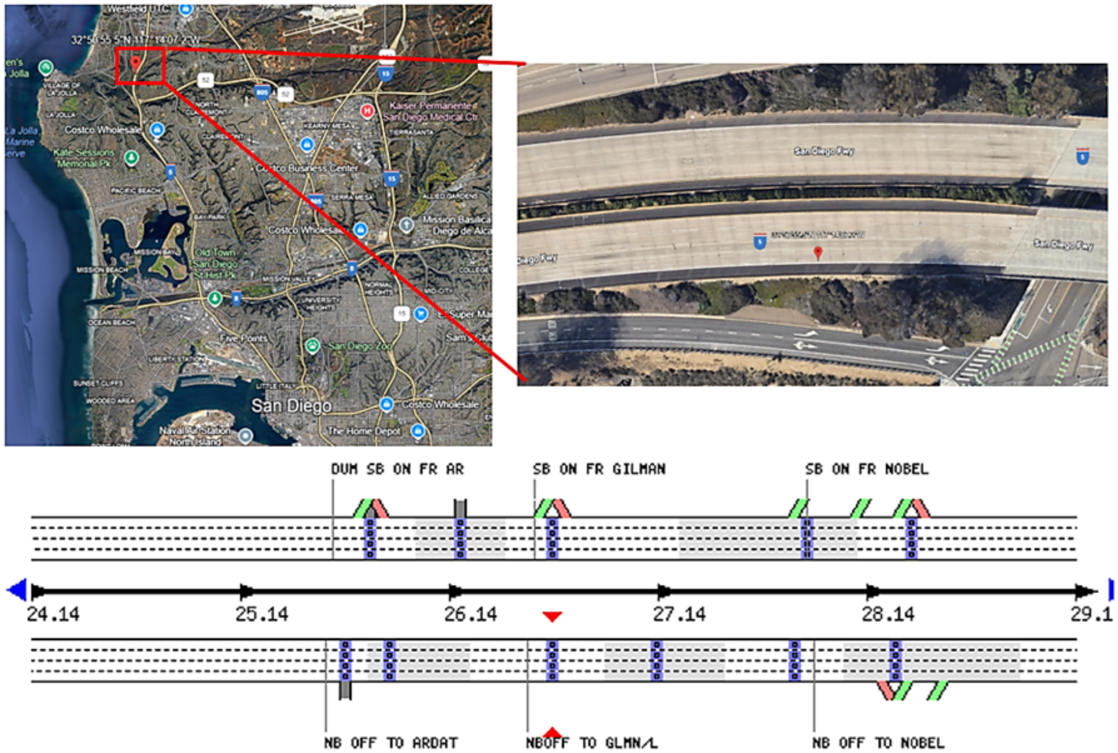


Figure 36. I-5 Freeway Segment in San Diego.

Table 9. Roadway Information of I-5 Freeway

Roadway Information	
Road Width	48 ft
Lane Width	12.0 ft
Inner Shoulder Width	8 ft
Inner Shoulder Treated Width	8 ft
Outer Shoulder Width	10 ft
Outer Shoulder Treated Width	10 ft
Design Speed Limit	70 mph
Functional Class	Principal Arterial
Inner Median Type	Unpaved
Inner Median Width	36 ft
Terrain	Rolling
Population	Urbanized
Barrier	Guardrail in Median Right Roadway
Surface	Concrete
Roadway Use	No Special Features

Additionally, the segment is equipped with vehicle detector stations, which are highlighted in blue, also in Figure 36. These stations include inductive loop detectors installed in each lane of the freeway. The purpose of these detectors is to collect, store, and process real-time traffic data continuously. The collected data is then transmitted to the Caltrans Performance Measurement System (PeMS) database for further analysis. The comprehensive data from these detectors allows for detailed monitoring and assessment of traffic patterns, congestion levels, and overall freeway performance under normal operating conditions. This setup ensures that the study can accurately capture the dynamics of freeway traffic flow with minimal external influences.

Given the study's focus on evaluating the effects of CAV technology within a work zone environment, the freeways data were specifically selected during periods where average speeds deviated moderately, approximately 15 miles per hour below the design speed limit. This deviation implies moderate traffic congestion prior to simulating a lane closure, thus offering a pertinent environment for examining the impacts of CAV technology. The study examined traffic patterns over a one-hour period during the morning peak, specifically from 8:15 AM to 9:15 AM, July 17, 2024. Table 10 presents the field traffic data, which has been aggregated to provide traffic volume and average speed in 5-minute intervals. As illustrated in Figure 37, the study area experienced notable congestion, with vehicle flow rates peaking at as high as 656 vehicles per 5-minute interval. Additionally, there was a noticeable decrease in speed during this time period, as shown in Figure 38.

Table 10. Traffic Speed and Traffic Flow on I-5 Freeway

	Flow (Veh / 5 Minutes)					**Speed (mph)**				
Time	Lane 1	Lane 2	Lane 3	Lane 4	Total	Lane 1	Lane 2	Lane 3	Lane 4	Average
8:20 AM	148	153	165	170	636	49.3	46.4	44.0	41.4	45.1
8:25 AM	151	156	169	174	650	51.5	48.5	45.7	43.1	47.0
8:30 AM	158	156	164	178	656	54.2	52.2	49.1	45.7	50.1
8:35 AM	130	138	143	146	557	45.9	44.4	40.9	35.8	41.6
8:40 AM	158	151	161	161	631	49.1	47.5	44.6	40.1	45.3
8:45 AM	143	148	143	150	584	49.3	48.1	45.3	41.0	45.9
8:50 AM	155	136	171	162	624	50.6	49.1	46.7	42.6	47.1
8:55 AM	149	139	151	151	590	51.0	50.3	47.2	43.2	47.9
9:00 AM	139	151	157	163	610	50.5	49.5	46.9	43.0	47.3
9:05 AM	144	134	164	156	598	51.0	49.3	47.1	43.4	47.6
9:10 AM	144	149	147	163	603	51.5	49.0	47.1	43.9	47.8
9:15 AM	140	147	155	171	613	54.3	52.9	50.3	47.1	50.9

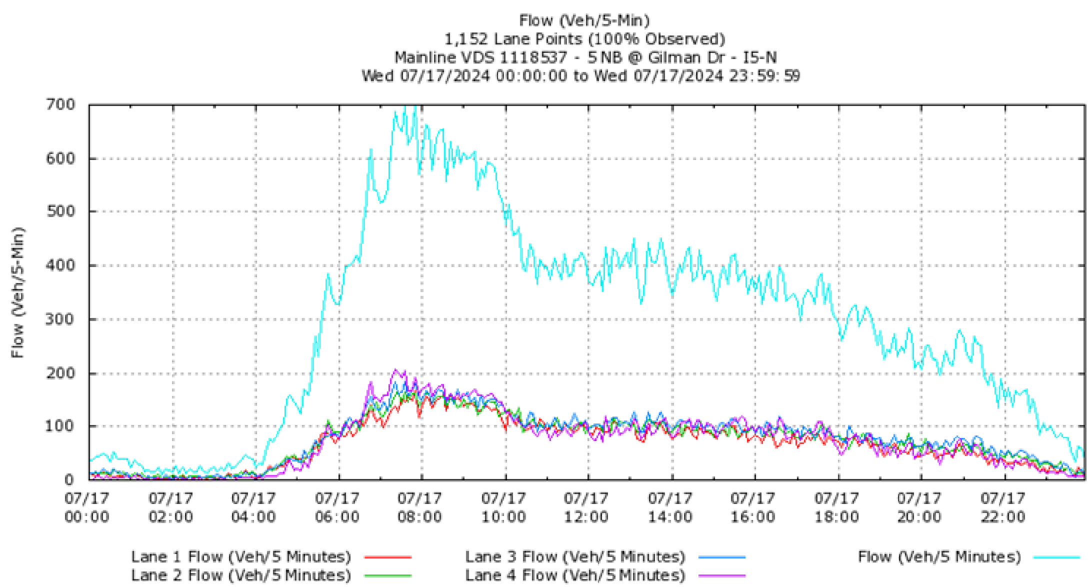


Figure 37. Observed Flow.

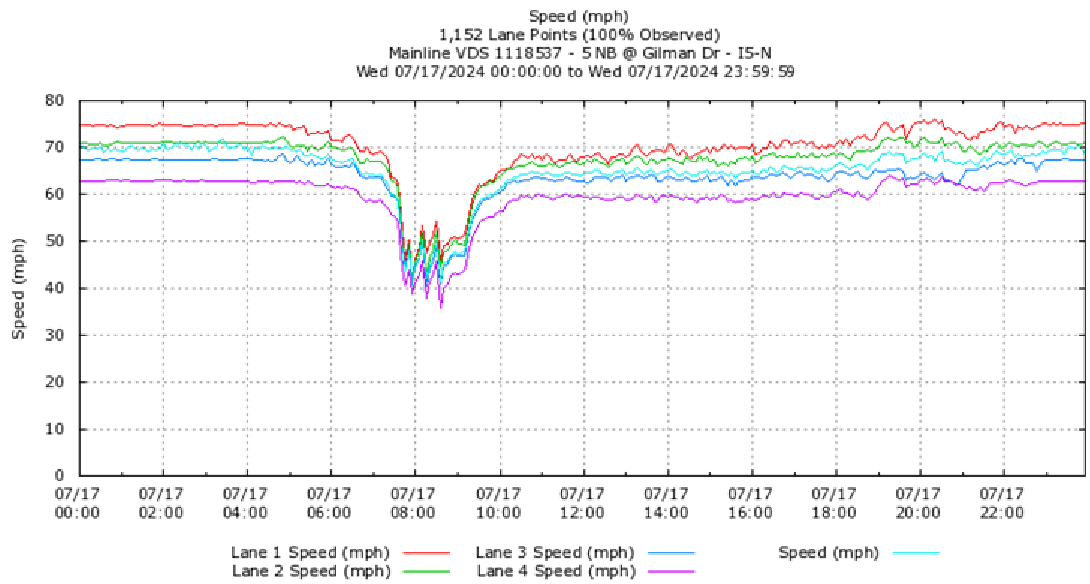


Figure 38. Observed Speed.

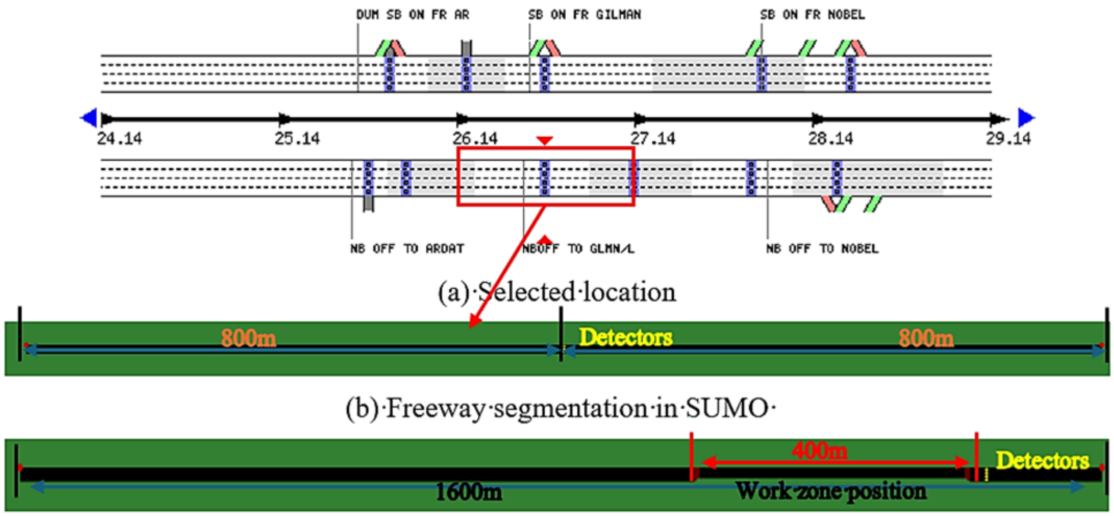
A.3.4 Summary This Chapter focuses on selecting freeway segments suitable for simulating work zone scenarios and gathering necessary data. Leveraging the Caltrans Performance Measurement System (PeMS) database due to data limitations in North Carolina, the study identified strategic freeway segment based on its traffic characteristics and lane configurations. Detailed descriptions and field data from selected segments provide insights into traffic patterns and dynamics essential for evaluating future work zone impacts and Connected and Autonomous Vehicle (CAV) technology effects.

A.4 Calibrating Parameters of the Microscopic Simulation Model

A.4.1 Introduction Microscopic traffic simulation, such as VISSIM, and SUMO, have been extensively utilized in transportation planning, design, and evaluation due to their advantages of being cost-effective, risk-free, and time efficient. To enhance the reliability and validity of microscopic traffic simulation outcomes, the simulation scenario should closely replicate the characteristics of real-world traffic flow, such as traffic volume and speed. While most simulation platforms provide default parameter values intended to represent typical traffic flow characteristics, these predefined settings frequently fall short in capturing the complexities observed in real-world traffic environments. Thus, rigorous calibration of model parameters is essential. However, due to the high dimensionality and complexity of the parameter space, this task is often time-consuming and challenging. Besides, due to lack of gradient information, traditional mathematical programming methods are ineffective. Thus, this chapter employs metaheuristic approaches such as Genetic Algorithm (GA), Simulated Annealing (SA) and Particle Swarm Optimization (PSO) to find the optimal set of parameters so that minimize discrepancies between observed and simulated traffic data.

This chapter is organized as follows. Section A.4.2 presents the configuration of work zone and basic settings in SUMO. Section A.4.3 formulates the objective function employed in the calibration. Section A.4.4 introduces the calibration process and three types of metaheuristic approaches. Section A.4.5 describes the set of parameters in SUMO being calibrated. Section A.4.6 presents the calibration results. Finally, Section A.4.7 provides a comprehensive summary and concluding insights into the chapter.

A.4.2 Simulation Setup This study uses SUMO to conduct the calibration process. According to the collected data, the simulation scenario is shown in Figure 39. Specifically, Figure 39(a) illustrates the real-world freeway segmentation configuration, Figure 39(b) presents the corresponding simulated configuration, and Figure 39(c) shows the simulated configuration with a work zone implemented. The traffic direction is from west to east, and the mainline section has 4 lanes. The speed limit for the mainline and work zone is 70 mph and 55 mph. Each simulation lasted for an hour of the a.m. peak, from 8:15 to 9:15 a.m. on July 17th, 2024. and the field traffic data (i.e. flow and speed) are aggregated into 5-min counts. The Wiedemann 99 car following model and the LC2013 lane-changing model are used.



(a) Selected location

(b) Freeway segmentation in SUMO

(c) Work zone settings in SUMO

Figure 39. Schematic of SUMO for Calibration and Performance Evaluation.

A.4.3 Objective Function To minimize the difference between real word traffic conditions and simulated traffic conditions, the parameters of the microscopic traffic simulation model need to be calibrated. Specifically, the calibration process aims to minimize the differences between the observed and simulated traffic data, such as traffic volumes, speed, and travel time. In this study, the objective function uses the Mean Absolute Normalized Error (MANE), which has been widely used in parametric calibration functions. The objective function can be defined as follows:

$$\begin{aligned} \min_{q,v} \quad & \mathrm{MANE}(q,v) = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{|q_{\mathrm{obs},i} - q_{\mathrm{sim},i}|}{q_{\mathrm{obs},i}} + \frac{|v_{\mathrm{obs},i} - v_{\mathrm{sim},i}|}{v_{\mathrm{obs},i}}\right) \\ \text{s.t.} \quad & l_{p_j} \le p_j \le u_{p_j}, \quad j = 1,\ldots,n \end{aligned} \tag{A.1}$$

Where:

- $q_{\mathrm{obs},i}$ and $v_{\mathrm{obs},i}$ denote the observed traffic flow and speed at time period i.
- $q_{\mathrm{sim},i}$ and $v_{\mathrm{sim},i}$ denote the simulated traffic flow and speed at time period i.
- p_j denotes the j-th model parameter to be calibrated.
- l_{p_j} and u_{p_j} denote the lower and upper bounds of parameter p_j, respectively.
- n is the total number of model parameters.
- N is the total number of observations.

A.4.4 Optimization Algorithms

A.4.4.1 Genetic Algorithm Genetic Algorithm (GA) is a heuristic optimization method based on the principles of natural selection and genetics [71]. Its basic principle is to simulate the process of biological evolution and optimize the solution space of the problem through selection, crossover and mutation. In the process of calibrating parameters of the car-following model, the genetic algorithm first randomly generates an initial population, in which each individual represents a combination of parameters, and each gene represents the parameter, and evaluates the individual's fitness through the objective function. An individual with high fitness will have a higher probability to participate in the reproduction process of the next generation. The selection operation picks individuals based on fitness. Then, the crossover operation simulates genetic recombination in nature, where the selected parent individuals exchange part of their genetic information to generate new offspring, thus exploring a wider solution space. To avoid the algorithm from falling into local optimal solutions, the mutation operation randomly changes some of the genes to increase the diversity of solutions. In each generation, the algorithm performs selection, crossover, and mutation operations through continuous iteration, and finally generates an individual with higher fitness as the optimal solution, as shown in Figure 40. The advantage of the genetic algorithm is that it does not rely on gradient information of the problem, and is suitable for solving complex, nonlinear optimization problems with strong global search capability [83, 196].

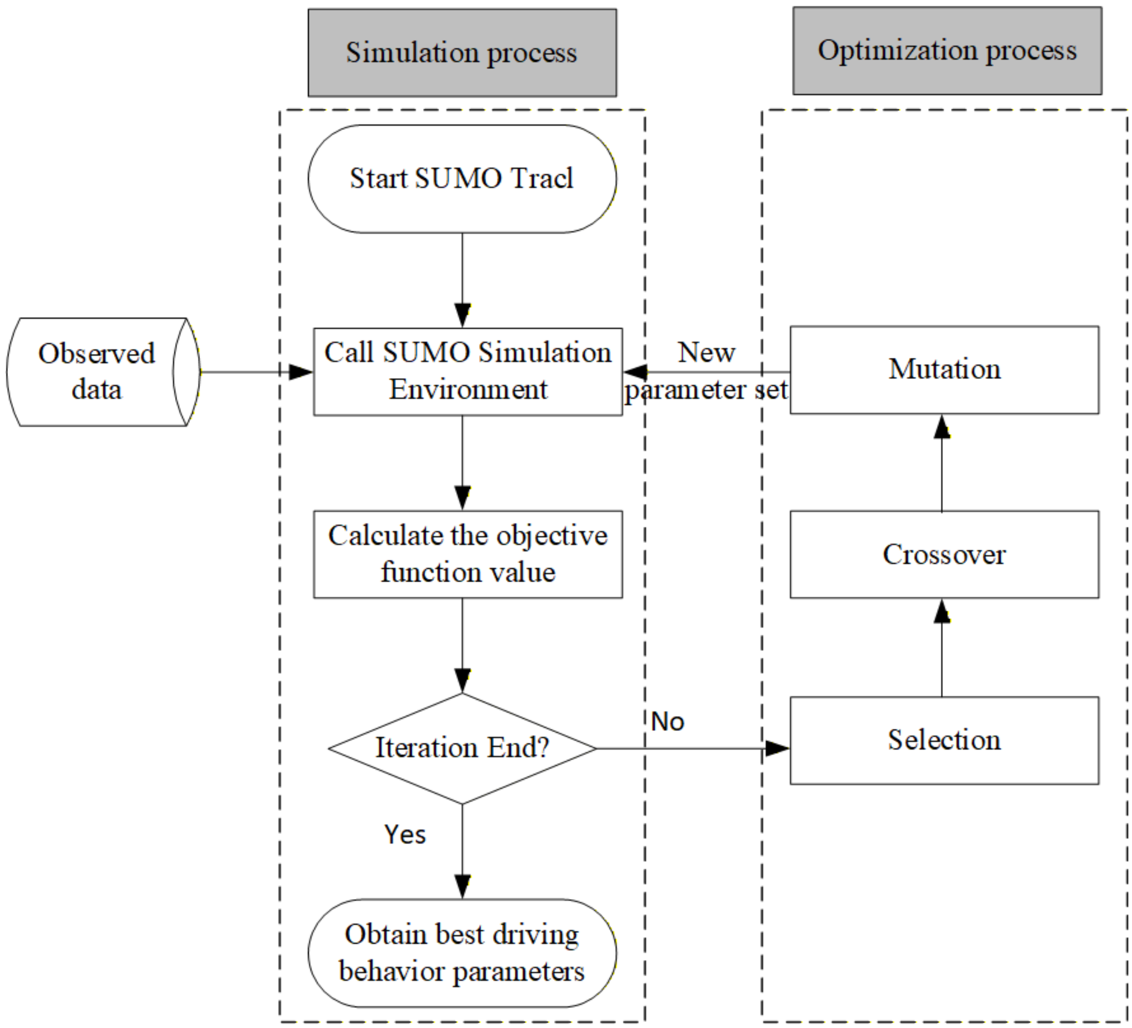


Figure 40. GA Calibration Process.

A.4.4.2 Simulated Annealing Simulated Annealing (SA) is a global optimization algorithm based on thermodynamic principles and is inspired by the energy evolution mechanism in the annealing process of metals. When calibrating the parameters of the car-following model in SUMO, the simulated annealing algorithm optimizes the parameters by randomly perturbing the parameter combinations and deciding whether to update the current solution or not according to certain acceptance criteria. In this research, it minimizes the difference between the simulation results and the actual traffic flow data. First, the algorithm initializes a parameter combination as the current solution and sets the initial temperature, which determines the perturbation amplitude and acceptance probability during the search process. Subsequently, in each round of iterations, the algorithm randomly generates a new solution in the parameter space and calculates the corresponding fitness value of this solution. If the fitness of the new solution is better than the current one, it is accepted directly, otherwise the worse solution is accepted with a certain probability. By gradually decreasing the temperature, the simulated annealing algorithm can explore a wider solution space in the early stage to avoid falling to the local optimum. And it can gradually converge to the optimal parameter combination in the later stage, which makes the calibration results more accurately. This process is shown in Figure 41. The advantage of this algorithm is that it has strong search ability and can find better solutions in high-dimensional complex optimization problems. However, the convergence speed depends on the initial temperature, the cooling rate and the termination conditions [183].

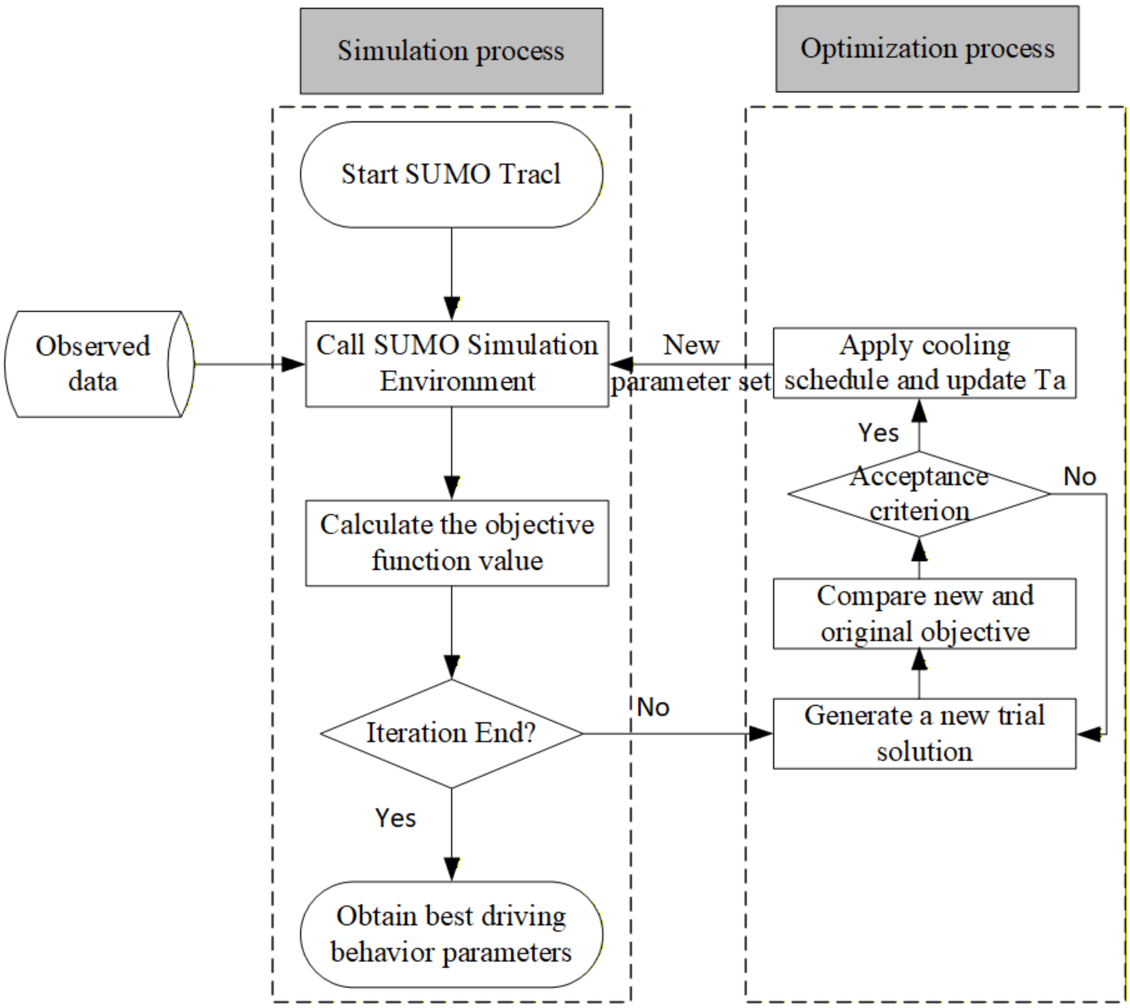


Figure 41. SA Calibration Process.

A.4.4.3 Particle Swarm Optimization Particle Swarm Optimization (PSO) is an optimization algorithm based on group intelligence, which is inspired by the foraging behavior of bird flocks and the social behavior of fish swimming [24]. When calibrating the parameters of the car-following model in SUMO, the particle swarm algorithm can effectively search the solution space and optimize the model parameters to make the simulation results more compatible with the actual traffic flow data. In the process, a set of particles is first randomly generated in the parameter space, each particle represents a combination of parameters, and the simulation results (objective function value) are calculated according to this parameter combination. Each particle has its own position and velocity, the position represents the current value of the parameter, and the velocity indicates how to adjust the parameter. The particle adjusts its position during the search process based on its own historical best solution as well as the global best solution among all the particles, and the update formula for the velocity combines personal experience (i.e., the deviation of the particle from its own best position) and social experience (i.e., the deviation of the particle from the global best position). Through many iterations, the particle swarm gradually approaches the optimal parameter solution and finally finds the parameter combination that best matches the traffic flow observation data. This process is shown in Figure 42. For the calibration of the parameters of the car-follow model in SUMO, the particle swarm algorithm can effectively explore the multi-dimensional parameter space to find the optimal solution, thus improving the accuracy and reliability of the model [181].

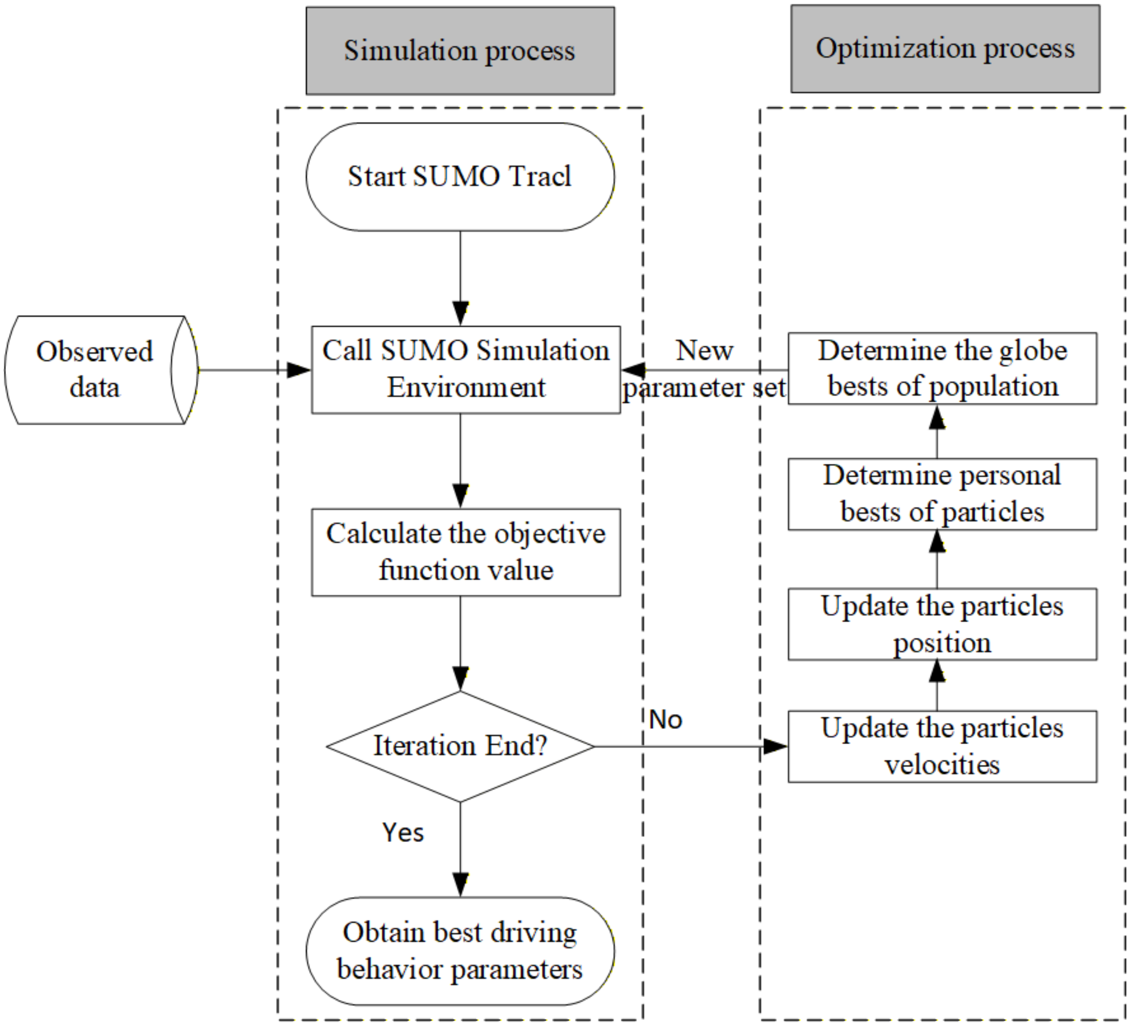


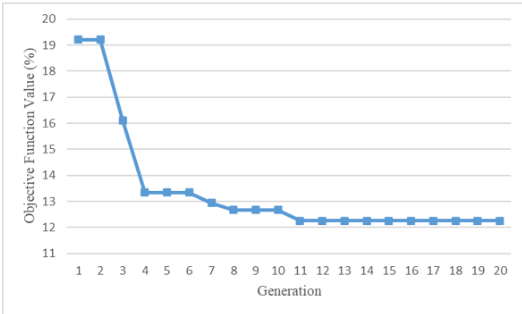
Figure 42. PSO Calibration Process.

A.4.5 SUMO Calibration Parameters Car-following models are a fundamental component of microscopic traffic simulation, representing how a vehicle adjusts its speed and acceleration based on the movement of a leading vehicle. The Wiedemann 99 model is a widely used psychophysical car-following model implemented in SUMO [11, 39]. As defined by Wiedemann 99 model, a vehicle has four primary driving states that describe different phases of interaction between the following vehicle and the lead vehicle [38]: (1) Free-Driving means that the leading vehicle is sufficiently far ahead, thus the following vehicle accelerates toward its desired speed without considering the leader's movement. (2) Approaching is defined as the following vehicle adjusting its speed when it perceives a speed difference with the lead vehicle. (3) Following means that the following vehicle maintains a steady speed while responding to small speed changes in the lead vehicle. (4) Braking is defined as the following vehicle applies emergency braking to avoid a collision. The Wiedemann 99 model can be calibrated by ten driving behavior parameters (i.e., CC0, CC1, . . . , CC9). The description and default values of these parameters are shown in Table 11.

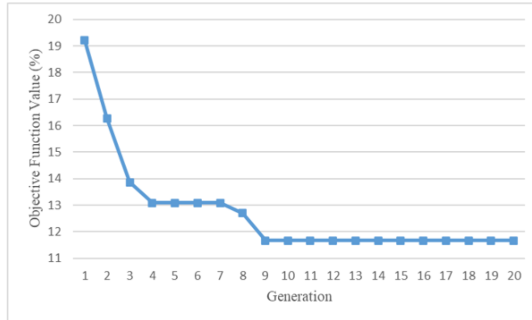
Table 11. Car Following Model Parameters

Parameter	Description	Default Values
CC0	The minimum gap is maintained between two stationary vehicles.	1.5 m
CC1	The desired time gap between vehicles while following.	1.30 s
CC2	Range of vehicle gap during the following regime.	8.00 m
CC3	The time between initiating deceleration upon detecting a slow-moving leader and transitioning into unconscious following behavior.	-12.00 s
CC4	Minimum relative speed threshold in relation to a slower leading vehicle during the following process.	-0.25 m/s
CC5	Upper threshold for relative speed compared to a faster leading vehicle during the following process.	0.35 m/s
CC6	The influence of distance on speed oscillation during the following process.	6.00 (1/m.s)
CC7	Actual acceleration during oscillation in the unconscious following regime.	0.25 m/s^2
CC8	Desired acceleration when the vehicle starts from the standing condition.	2.00 m/s^2
CC9	Desired acceleration at 80 km/h, though limited by maximum acceleration for the vehicle type.	1.50 m/s^2

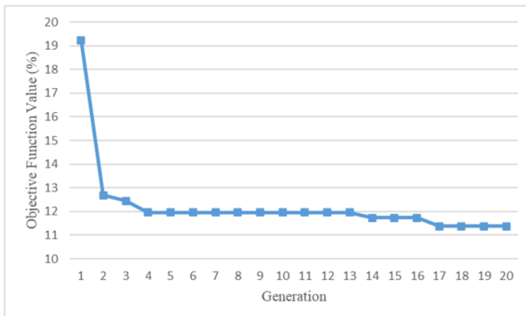
A.4.6 Calibration Results Figure 43(a) shows the calibration process by the GA. The y-axis represents be objective function (MANE value) and the x-axis denotes the number of generations. To ensure the algorithm's search ability in the solution space, the parameters in GA are repeated tests and the number of the crossover probability, mutation probability, population size, and generations were set at 0.9, 0.2, 20 and 20. The first iteration is the MANE value obtained using the default parameters. Under these default parameters, the MANE value is 19.2%, which means that the simulation environment does not reflect the real traffic conditions well. As the iteration progresses, the MANE value decreases and stabilizes at 12.3% at the 11th iteration. Figure 43(b) shows the calibration process by the SA. Similarly, after multiple tests, the parameters of the SA algorithm are set as follows: stopping temperature=1e-7; initial temperature=100; iterations=20; maximum stay counter=15. From this figure, the MANE value decreases until it stabilized at 11.67% in the ninth generation. Figure 43(c) shows the calibration process by the PSO. At the beginning, the MANE value decreases rapidly, which reflects the global search capability of the PSO algorithm. The parameters of the PSO algorithm are set as follows: population size=20; maximum Iterations=20; weight=0.8; learning parameter 1=0.5; learning parameter 2=0.5. When iterating to 17 generations, the MANE value stabilizes at 11.38% and achieves the optimal result among the three algorithms. Therefore, we choose the results of PSO algorithms as the optimal parameters for the simulation environment, as shown in Table 12.



(a)·GA-based·calibration·process



(b)·SA-based·calibration·process



(c)·PSO-based·calibration·process

Figure 43. Values of Objective Function MANE During the Optimization Period.

Table 12. Calibration Results of the Car Following Model Parameters

Parameter	**Description**	**Values**	**Lower boundary**	**Upper boundary**
CC0	Standstill distance (m)	0.957	0	2.5
CC1	Headway time (s)	1.000	1	2.5
CC2	Following variation (m)	9.900	6	10
CC3	Threshold for entering following (s)	-10.713	-15	-10
CC4	Negative following threshold (m/s)	-0.159	-0.4	-0.1
CC5	Positive following threshold (m/s)	0.262	0.2	0.5
CC6	Speed dependency of oscillation (10^{-4} rad/s)	4.200	4	8
CC7	Oscillation acceleration (m/s^2)	0.368	0.1	0.4
CC8	Standstill acceleration (m/s^2)	4.289	1	4.5
CC9	Acceleration at 80 km/h (m/s^2)	2.093	0.5	4.5

A.4.7 Summary This chapter introduces the simulation settings, calibration process of the microscopic simulation model and three types of optimization algorithms. A comparative analysis of the calibration results for the three algorithms reveals that the parameters optimized through PSO demonstrate superior performance, achieving a MANE value of 11.38%, which is notably better than the default parameters, which resulted in a MANE value of 19.2%. Although we tried several experiments without obtaining better results than the current one, there is still space for improvement in the current optimization strategy. For example, some emerging optimization algorithms, such as the Grey Wolf Optimizer and Whale Optimization Algorithm, or warm-start methods that use solutions obtained from one algorithm as starting points for another, may get better solutions. In the future, we will further investigate these issues.

A.5 Numerical Results

A.5.1 Introduction This chapter presents the numerical results obtained from the simulations conducted in this study. The analysis considers three types of vehicles: Human-Driven Vehicles (HDVs), Autonomous Vehicles (AVs), and Connected and Autonomous Vehicles (CAVs). To accurately represent their driving behavior, different car-following models were employed. The calibrated Wiedemann 99 model was used for HDVs, the Intelligent Driver Model (IDM) was applied to AVs, and the Cooperative Adaptive Cruise Control (CACC) model was implemented for CAVs. Two primary lane-reduction scenarios were examined, consisting of a single-lane drop and a dual-lane drop. The impact of AV and CAV integration on freeway operations was evaluated under varying market penetration rates and traffic demand levels, with particular attention to safety, mobility, and environmental performance.

A.5.2 Numerical Results Building upon the potential freeway segments, a four-lane (unidirectional) freeway segment was selected from the Caltrans Performance Measurement System (PeMS) for detailed analysis. This segment was selected due to its suitability for evaluating the effects of multi-lane drop scenarios. Three distinct traffic demand levels were defined for the simulation: low demand, representing the minimum observed hourly traffic volume during the day; high demand, corresponding to the peak hourly volume; and medium demand, calculated as the median value between the low and high demand levels. The impact of AVs and CAVs on the selected segment is assessed across a range of market penetration rates. The corresponding numerical results are presented and discussed in the subsequent sections.

A.5.2.1 Single Lane Drop

A.5.2.1.1 Low Demand As outlined previously, simulation metrics related to safety (Time-to-Collision ¡ 3.0 seconds), mobility (work zone throughput and average speed), and environmental performance (greenhouse gas emissions and air pollutant levels) were collected at each simulation step. In addition, the percentage change in each metric relative to a baseline scenario consisting of 100% human-driven vehicles were presented in parentheses. Analyses were conducted across a range of AV and CAV market penetration rates, increasing in 10% increments. The empirical traffic demand corresponding to this scenario is 4,676 vehicles per hour. Figure 44 shows the safety-related metric under different penetration level of CAVs and AVs. In a fully CAV environment, the Time-to-Collision (TTC) metric improves by only 6.8% relative to the baseline. In contrast, a fully AV environment results in a more pronounced improvement, with TTC decreasing by 34%. The simulation results suggest that the benefits of CAVs are limited under low-demand conditions. This outcome can be attributed to the absence of significant congestion, which reduces the operational advantages typically offered by advanced vehicle technologies. Mobility-related metrics, including work zone throughput (as shown in Figure 45) and mean speed (as shown in Figure 46), show minimal variation across the different vehicle technologies. Specifically, the mean speed remains within a 4% deviation from the fully human-driven baseline, while work zone throughput fluctuates by no more than 0.05% across scenarios involving HDVs, AVs, and CAVs. In contrast, the impacts of CAV and AV on environmental metrics are more substantial, as shown in Figure 47. A fully AV environment yields a 22% reduction in greenhouse gas (GHG) emissions, specifically in carbon dioxide (CO_2) and carbon monoxide (CO), while a 100% CAV scenario results in an 17.3% reduction. Similarly, according to Figure 48, fully AV and fully CAV environments yield reductions in air pollutants by 30% and 22.55%, respectively. These findings underscore the environmental advantages of AV and CAV technologies, even in conditions where their contributions to safety and mobility are comparatively limited.

CAV \ AV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	90437 (0.00%)	87390 (-3.37%)	85311 (-5.67%)	79640 (-11.94%)	77518 (-14.29%)	77766 (-14.01%)	73542 (-18.68%)	65661 (-27.40%)	63372 (-29.93%)	63430 (-29.86%)	59597 (-34.10%)
10%	88546 (-2.09%)	85493 (-5.47%)	84968 (-6.05%)	81237 (-10.17%)	74991 (-17.08%)	73529 (-18.70%)	69794 (-22.83%)	69206 (-23.48%)	64374 (-28.82%)	62778 (-30.58%)	
20%	87707 (-3.02%)	84948 (-6.07%)	84012 (-7.10%)	78022 (-13.73%)	71946 (-20.45%)	72709 (-19.60%)	71343 (-21.11%)	67161 (-25.74%)	62967 (-30.37%)		
30%	86012 (-4.89%)	85185 (-5.81%)	82382 (-8.91%)	76752 (-15.13%)	72914 (-19.38%)	70888 (-21.62%)	68416 (-24.35%)	64065 (-29.16%)			
40%	84311 (-6.77%)	84357 (-6.72%)	76957 (-14.91%)	74904 (-17.18%)	71850 (-20.55%)	69295 (-23.38%)	68179 (-24.61%)				
50%	84086 (-7.02%)	83051 (-8.17%)	78117 (-13.62%)	77755 (-14.02%)	70689 (-21.84%)	67635 (-25.21%)					
60%	80808 (-10.65%)	80928 (-10.51%)	76708 (-15.18%)	74223 (-17.93%)	66177 (-26.83%)						
70%	80127 (-11.40%)	78317 (-13.40%)	75700 (-16.30%)	69822 (-22.79%)							
80%	79395 (-12.21%)	82698 (-8.56%)	75593 (-16.41%)								
90%	84991 (-6.02%)	83207 (-7.99%)									
100%	84220 (-6.87%)										

Figure 44. Critical Time-to-Collision Counts Under Low Traffic Demand Scenario (Single Lane Drop)

CAV \ AV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	4674 (0.00%)	4676 (0.04%)	4676 (0.04%)	4673 (-0.02%)	4674 (0.00%)	4673 (-0.02%)	4674 (0.00%)	4673 (-0.02%)	4676 (0.04%)	4676 (0.04%)	4674 (0.00%)
10%	4675 (0.02%)	4675 (0.02%)	4673 (-0.02%)	4673 (-0.02%)	4673 (-0.02%)	4673 (-0.02%)	4673 (-0.02%)	4673 (-0.02%)	4675 (0.02%)	4676 (0.04%)	
20%	4676 (0.04%)	4673 (-0.02%)	4674 (0.00%)	4673 (-0.02%)	4674 (0.00%)	4673 (-0.02%)	4674 (0.00%)	4673 (-0.02%)	4676 (0.04%)		
30%	4673 (-0.02%)	4673 (-0.02%)	4673 (-0.02%)	4673 (-0.02%)	4673 (-0.02%)	4673 (-0.02%)	4673 (-0.02%)	4673 (-0.02%)			
40%	4674 (0.00%)	4673 (-0.02%)	4674 (0.00%)	4673 (-0.02%)	4674 (0.00%)	4673 (-0.02%)	4674 (0.00%)				
50%	4673 (-0.02%)	4673 (-0.02%)	4673 (-0.02%)	4673 (-0.02%)	4673 (-0.02%)	4673 (-0.02%)					
60%	4674 (0.00%)	4673 (-0.02%)	4674 (0.00%)	4673 (-0.02%)	4674 (0.00%)						
70%	4673 (-0.02%)	4673 (-0.02%)	4673 (-0.02%)	4673 (-0.02%)							
80%	4676 (0.04%)	4675 (0.02%)	4676 (0.04%)								
90%	4676 (0.04%)	4676 (0.04%)									
100%	4674 (0.00%)										

Figure 45. Work Zone Throughput (Veh/hr) Under Low Traffic Demand Scenario (Single Lane Drop)

AV / CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	61.88 (0.00%)	61.87 (-0.02%)	61.17 (-1.15%)	60.76 (-1.81%)	60.59 (-2.08%)	60.05 (-2.96%)	59.3 (-4.17%)	59.57 (-3.73%)	59.23 (-4.28%)	59.69 (-3.54%)	59.4 (-4.01%)
10%	62.16 (0.45%)	61.43 (-0.73%)	61.78 (-0.16%)	61.2 (-1.10%)	60.38 (-2.42%)	60.31 (-2.54%)	59.95 (-3.12%)	60.04 (-2.97%)	59.6 (-3.68%)	59.12 (-4.46%)	
20%	62.2 (0.52%)	61.85 (-0.05%)	61.65 (-0.37%)	61.18 (-1.13%)	60.78 (-1.78%)	60.4 (-2.39%)	60.45 (-2.31%)	59.72 (-3.49%)	59.44 (-3.94%)		
30%	62.3 (0.68%)	61.83 (-0.08%)	61.41 (-0.76%)	61.09 (-1.28%)	60.56 (-2.13%)	60.51 (-2.21%)	60.18 (-2.75%)	60.01 (-3.02%)			
40%	62.41 (0.86%)	62.14 (0.42%)	61.61 (-0.44%)	61.36 (-0.84%)	60.79 (-1.76%)	60.36 (-2.46%)	60.29 (-2.57%)				
50%	62.55 (1.08%)	62.28 (0.65%)	61.58 (-0.48%)	61.38 (-0.81%)	61.16 (-1.16%)	60.94 (-1.52%)					
60%	62.54 (1.07%)	62.44 (0.90%)	61.94 (0.10%)	61.73 (-0.24%)	61.42 (-0.74%)						
70%	62.88 (1.62%)	62.64 (1.23%)	62.3 (0.68%)	61.75 (-0.21%)							
80%	62.88 (1.62%)	62.59 (1.15%)	62.29 (0.66%)								
90%	63.35 (2.38%)	63.1 (1.97%)									
100%	63.84 (3.17%)										

Figure 46. Mean Speed (MPH) Under Low Traffic Demand Scenario (Single Lane Drop)

AV / CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	1908.99 (0.00%)	1878.66 (-1.59%)	1841.51 (-3.53%)	1799.26 (-5.75%)	1753.46 (-8.15%)	1685.42 (-11.71%)	1668.36 (-12.61%)	1601.86 (-16.09%)	1564.57 (-18.04%)	1525.3 (-20.10%)	1489.09 (-22.00%)
10%	1886.18 (-1.19%)	1853.61 (-2.90%)	1814.39 (-4.96%)	1749.88 (-8.33%)	1726.33 (-9.57%)	1670.84 (-12.48%)	1609.01 (-15.71%)	1577.67 (-17.36%)	1546.75 (-18.98%)	1512.86 (-20.75%)	
20%	1867.93 (-2.15%)	1814.49 (-4.95%)	1768.74 (-7.35%)	1721.17 (-9.84%)	1678.41 (-12.08%)	1629.34 (-14.65%)	1591.32 (-16.64%)	1555.27 (-18.53%)	1522.33 (-20.25%)		
30%	1834.63 (-3.90%)	1787.15 (-6.38%)	1733.35 (-9.20%)	1682.6 (-11.86%)	1640.1 (-14.09%)	1593.09 (-16.55%)	1557.99 (-18.39%)	1525.07 (-20.11%)			
40%	1802.15 (-5.60%)	1762.12 (-7.69%)	1687.2 (-11.62%)	1643.41 (-13.91%)	1594.61 (-16.47%)	1563.78 (-18.08%)	1527.36 (-19.99%)				
50%	1749.86 (-8.34%)	1726.06 (-9.58%)	1657.42 (-13.18%)	1608.84 (-15.72%)	1571.84 (-17.66%)	1513.52 (-20.72%)					
60%	1707.77 (-10.54%)	1671.53 (-12.44%)	1620.55 (-15.11%)	1581.07 (-17.18%)	1521.1 (-20.32%)						
70%	1670.99 (-12.47%)	1615.13 (-15.39%)	1579.91 (-17.24%)	1536.66 (-19.50%)							
80%	1638.31 (-14.18%)	1604.38 (-15.96%)	1571.96 (-17.65%)								
90%	1620.02 (-15.14%)	1577.83 (-17.35%)									
100%	1578.26 (-17.32%)										

Figure 47. Green House Gas Emission(kg) (CO2 and CO) Under Low Traffic Demand Scenario (Single Lane Drop)

CAV \ AV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	0.9254 (0.00%)	0.9057 (-2.13%)	0.882 (-4.69%)	0.8549 (-7.62%)	0.826 (-10.74%)	0.782 (-15.50%)	0.7687 (-16.93%)	0.7248 (-21.68%)	0.6982 (-24.55%)	0.6719 (-27.39%)	0.6475 (-30.03%)
10%	0.9094 (-1.73%)	0.89 (-3.83%)	0.8642 (-6.61%)	0.8237 (-10.99%)	0.8067 (-12.83%)	0.7714 (-16.64%)	0.7304 (-21.07%)	0.7082 (-23.47%)	0.6865 (-25.82%)	0.663 (-28.36%)	
20%	0.8973 (-3.04%)	0.8641 (-6.62%)	0.8345 (-9.82%)	0.8044 (-13.08%)	0.7769 (-16.05%)	0.7441 (-19.59%)	0.7183 (-22.38%)	0.6931 (-25.10%)	0.6703 (-27.57%)		
30%	0.8757 (-5.37%)	0.8461 (-8.57%)	0.8121 (-12.24%)	0.7798 (-15.73%)	0.7513 (-18.81%)	0.7197 (-22.23%)	0.6971 (-24.67%)	0.6742 (-27.15%)			
40%	0.8552 (-7.59%)	0.8301 (-10.30%)	0.7829 (-15.40%)	0.754 (-18.52%)	0.7228 (-21.89%)	0.7012 (-24.23%)	0.6772 (-26.82%)				
50%	0.8231 (-11.05%)	0.8073 (-12.76%)	0.7634 (-17.51%)	0.7322 (-20.88%)	0.7079 (-23.50%)	0.6712 (-27.47%)					
60%	0.7951 (-14.08%)	0.774 (-16.36%)	0.7412 (-19.90%)	0.716 (-22.63%)	0.6772 (-26.82%)						
70%	0.773 (-16.47%)	0.7374 (-20.32%)	0.7148 (-22.76%)	0.689 (-25.55%)							
80%	0.7535 (-18.58%)	0.732 (-20.90%)	0.7122 (-23.04%)								
90%	0.7421 (-19.81%)	0.716 (-22.63%)									
100%	0.7167 (-22.55%)										

Figure 48. Air Pollution (Kg) (NOx, HC, PMx) Under Low Traffic Demand Scenario (Single Lane Drop)

A.5.2.1.2 Medium Demand To enhance the robustness of the analysis, additional simulations were conducted under a medium-demand condition. This scenario was defined as the median of the empirically observed high- and low-demand levels, corresponding to an input volume of 6,014 vehicles per hour. According to Figures 49 , the simulation results indicate that safety benefits become more pronounced at this intermediate demand level. In particular, the Time-to-Collision (TTC) metric shows a relatively consistent and progressive reduction with increasing market penetration of AVs and CAVs. Under full adoption, a 100% AV environment reduces TTC by 86%, while a fully CAV environment achieves a 54% reduction compared to the baseline of human-driven vehicles. Mobility metrics remain relatively stable across all scenarios, as shown in Figure 50 and 51. Work zone throughput, in particular, exhibits less than a 1% deviation from the human-driven baseline, suggesting that the medium demand level does not induce significant congestion or operational delays. Consistent with findings from the low-demand scenario, environmental benefits are substantial. Greenhouse gas (GHG) emissions (as shown in Figure 52) are reduced by 48% in a fully AV environment and by 43% in a fully CAV environment. Similarly, air pollution levels (as shown in Figure 53) decline by 58% and 51% for fully AV and CAV scenarios, respectively. These results reinforce the potential of AVs and CAVs to contribute meaningfully to safety and environmental sustainability, even in the absence of major mobility improvements.

AV / CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	333205 (0.00%)	327997 (-1.56%)	291062 (-12.65%)	255142 (-23.43%)	199435 (-40.15%)	140423 (-57.86%)	110386 (-66.87%)	85800 (-74.25%)	64256 (-80.72%)	53683 (-83.89%)	45401 (-86.37%)
10%	288470 (-13.43%)	281431 (-15.54%)	220684 (-33.77%)	178997 (-46.28%)	131143 (-60.64%)	108009 (-67.58%)	93788 (-71.85%)	66786 (-79.96%)	55305 (-83.40%)	43433 (-86.97%)	
20%	232288 (-30.29%)	212208 (-36.31%)	150026 (-54.97%)	128031 (-61.58%)	108213 (-67.52%)	90817 (-72.74%)	74573 (-77.62%)	63856 (-80.84%)	52439 (-84.26%)		
30%	186620 (-43.99%)	162176 (-51.33%)	146295 (-56.09%)	110409 (-66.86%)	104370 (-68.68%)	85930 (-74.21%)	72488 (-78.25%)	57122 (-82.86%)			
40%	171809 (-48.44%)	152537 (-54.22%)	127490 (-61.74%)	104342 (-68.69%)	90754 (-72.76%)	79380 (-76.18%)	66949 (-79.91%)				
50%	152735 (-54.16%)	140829 (-57.74%)	118237 (-64.52%)	101974 (-69.40%)	90252 (-72.91%)	71648 (-78.50%)					
60%	153838 (-53.83%)	136011 (-59.18%)	124028 (-62.78%)	99936 (-70.01%)	85508 (-74.34%)						
70%	144671 (-56.58%)	142302 (-57.29%)	121190 (-63.63%)	105095 (-68.46%)							
80%	161213 (-51.62%)	138735 (-58.36%)	135899 (-59.21%)								
90%	154362 (-53.67%)	142684 (-57.18%)									
100%	153956 (-53.80%)										

Figure 49. Critical Time-to-Collision Counts Under Medium Traffic Demand Scenario (Single Lane Drop)

AV / CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	5961 (0.00%)	5982 (0.35%)	6005 (0.74%)	6005 (0.74%)	6012 (0.86%)	6014 (0.89%)	6013 (0.87%)	6014 (0.89%)	6014 (0.89%)	6014 (0.89%)	6010 (0.82%)
10%	5993 (0.54%)	6001 (0.67%)	6012 (0.86%)	6008 (0.79%)	6014 (0.89%)	6014 (0.89%)	6012 (0.86%)	6013 (0.87%)	6014 (0.89%)	6014 (0.89%)	
20%	6008 (0.79%)	6010 (0.82%)	6009 (0.81%)	6013 (0.87%)	6014 (0.89%)	6012 (0.86%)	6011 (0.84%)	6013 (0.87%)	6014 (0.89%)		
30%	6011 (0.84%)	6011 (0.84%)	6012 (0.86%)	6014 (0.89%)	6014 (0.89%)	6011 (0.84%)	6012 (0.86%)	6014 (0.89%)			
40%	6009 (0.81%)	6012 (0.86%)	6014 (0.89%)	6013 (0.87%)	6012 (0.86%)	6014 (0.89%)	6013 (0.87%)				
50%	6013 (0.87%)	6012 (0.86%)	6012 (0.86%)	6013 (0.87%)	6013 (0.87%)	6014 (0.89%)					
60%	6013 (0.87%)	6011 (0.84%)	6009 (0.81%)	6012 (0.86%)	6011 (0.84%)						
70%	6014 (0.89%)	6012 (0.86%)	6011 (0.84%)	6012 (0.86%)							
80%	6012 (0.86%)	6013 (0.87%)	6012 (0.86%)								
90%	6013 (0.87%)	6012 (0.86%)									
100%	6008 (0.79%)										

Figure 50. Work Zone Throughput (Veh/hr) Under Medium Traffic Demand Scenario (Single Lane Drop)

AV CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	46.15 (0.00%)	46.6 (0.98%)	50.55 (9.53%)	50.48 (9.38%)	54.28 (17.62%)	55.37 (19.98%)	54.58 (18.27%)	55.17 (19.54%)	54.18 (17.40%)	54.16 (17.36%)	55.28 (19.78%)
10%	50.44 (9.30%)	51.79 (12.22%)	54.97 (19.11%)	56.14 (21.65%)	55.96 (21.26%)	55.91 (21.15%)	55.49 (20.24%)	55.15 (19.50%)	55.01 (19.20%)	54.62 (18.35%)	
20%	55.33 (19.89%)	55.97 (21.28%)	57.16 (23.86%)	56.59 (22.62%)	56.56 (22.56%)	56.24 (21.86%)	55.91 (21.15%)	55.59 (20.46%)	54.78 (18.70%)		
30%	57.25 (24.05%)	57.57 (24.75%)	57.18 (23.90%)	57.57 (24.75%)	56.88 (23.25%)	56.53 (22.49%)	55.93 (21.19%)	55.91 (21.15%)			
40%	57.89 (25.44%)	58.01 (25.70%)	57.71 (25.05%)	57.74 (25.11%)	57.17 (23.88%)	56.49 (22.41%)	56.75 (22.97%)				
50%	58.57 (26.91%)	57.81 (25.27%)	58.01 (25.70%)	57.79 (25.22%)	57.4 (24.38%)	57.04 (23.60%)					
60%	58.75 (27.30%)	58.15 (26.00%)	57.75 (25.14%)	57.9 (25.46%)	57.59 (24.79%)						
70%	59.64 (29.23%)	58.56 (26.89%)	58.18 (26.07%)	58.52 (26.80%)							
80%	59.31 (28.52%)	59.63 (29.21%)	58.56 (26.89%)								
90%	60.18 (30.40%)	59.84 (29.66%)									
100%	60.92 (32.00%)										

Figure 51. Mean Speed (MPH) Under Medium Traffic Demand Scenario (Single Lane Drop)

AV CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	3796.68 (0.00%)	3670.42 (-3.33%)	3395.1 (-10.58%)	3168.47 (-16.55%)	2895.58 (-23.73%)	2596.31 (-31.62%)	2441.93 (-35.68%)	2280.2 (-39.94%)	2152.28 (-43.31%)	2061.08 (-45.71%)	1964.79 (-48.25%)
10%	3537.88 (-6.82%)	3467.83 (-8.66%)	3114.76 (-17.96%)	2856.99 (-24.75%)	2583.64 (-31.95%)	2445.99 (-35.58%)	2326.89 (-38.71%)	2173.69 (-42.75%)	2087.77 (-45.01%)	2000.99 (-47.30%)	
20%	3227.38 (-14.99%)	3090.63 (-18.60%)	2756.88 (-27.39%)	2581.57 (-32.00%)	2446.21 (-35.57%)	2310.29 (-39.15%)	2188.72 (-42.35%)	2106.01 (-44.53%)	2022.35 (-46.73%)		
30%	2957.39 (-22.11%)	2769.51 (-27.05%)	2629.79 (-30.73%)	2427.87 (-36.05%)	2337.54 (-38.43%)	2215.04 (-41.66%)	2119.48 (-44.18%)	2039.54 (-46.28%)			
40%	2796.46 (-26.34%)	2603.84 (-31.42%)	2485.22 (-34.54%)	2329.3 (-38.65%)	2219.1 (-41.55%)	2125.24 (-44.02%)	2044.01 (-46.16%)				
50%	2606 (-31.36%)	2504.38 (-34.04%)	2348.46 (-38.14%)	2226.95 (-41.34%)	2134.92 (-43.77%)	2004.1 (-47.21%)					
60%	2562.14 (-32.52%)	2400.56 (-36.77%)	2295.01 (-39.55%)	2169.37 (-42.86%)	2041.67 (-46.22%)						
70%	2393.58 (-36.96%)	2324.95 (-38.76%)	2205.92 (-41.90%)	2108.03 (-44.48%)							
80%	2371.12 (-37.55%)	2228.21 (-41.31%)	2164.66 (-42.99%)								
90%	2226.71 (-41.35%)	2136.63 (-43.72%)									
100%	2145.31 (-43.50%)										

Figure 52. Green House Gas Emission(kg) (CO2 and CO) Under Medium Traffic Demand Scenario (Single Lane Drop)

AV / CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	2.017 (0.00%)	1.9365 (-3.99%)	1.7647 (-12.51%)	1.6234 (-19.51%)	1.4538 (-27.92%)	1.268 (-37.13%)	1.1683 (-42.08%)	1.063 (-47.30%)	0.9779 (-51.52%)	0.9172 (-54.53%)	0.8531 (-57.70%)
10%	1.8575 (-7.91%)	1.8112 (-10.20%)	1.5937 (-20.99%)	1.4333 (-28.94%)	1.2611 (-37.48%)	1.1723 (-41.88%)	1.0951 (-45.71%)	0.9939 (-50.72%)	0.9355 (-53.62%)	0.8775 (-56.49%)	
20%	1.6657 (-17.42%)	1.5804 (-21.65%)	1.3734 (-31.91%)	1.2616 (-37.45%)	1.1747 (-41.76%)	1.0858 (-46.17%)	1.0068 (-50.08%)	0.9499 (-52.91%)	0.8922 (-55.77%)		
30%	1.4994 (-25.66%)	1.3809 (-31.54%)	1.2931 (-35.89%)	1.1653 (-42.23%)	1.1068 (-45.13%)	1.025 (-49.18%)	0.9621 (-52.30%)	0.9077 (-55.00%)			
40%	1.3998 (-30.60%)	1.2792 (-36.58%)	1.2043 (-40.29%)	1.1044 (-45.25%)	1.0315 (-48.86%)	0.9686 (-51.98%)	0.9148 (-54.65%)				
50%	1.2821 (-36.44%)	1.2165 (-39.69%)	1.1178 (-44.58%)	1.0396 (-48.46%)	0.979 (-51.46%)	0.8959 (-55.58%)					
60%	1.2547 (-37.79%)	1.1525 (-42.86%)	1.0864 (-46.14%)	1.0055 (-50.15%)	0.9246 (-54.16%)						
70%	1.1504 (-42.96%)	1.1071 (-45.11%)	1.0314 (-48.86%)	0.9703 (-51.89%)							
80%	1.1366 (-43.65%)	1.0478 (-48.05%)	1.0066 (-50.09%)								
90%	1.0472 (-48.08%)	0.9908 (-50.88%)									
100%	0.9972 (-50.56%)										

Figure 53. Air Pollution (Kg) (NOx, HC, PMx) Under Medium Traffic Demand Scenario (Single Lane Drop)

A.5.2.1.3 High Demand Traffic volume was increased to the highest observed demand level for the study day, corresponding to an input value of 7,352 vehicles per hour in the SUMO simulation. Under this high-demand condition, CAVs exhibited superior overall performance. In terms of safety in Figure 54, surrogate conflict counts based on Time-to-Collision (TTC) metrics were reduced by 12% in a fully AV environment and by 63% in a fully CAV environment, indicating the added benefit of vehicle connectivity in mitigating crash risk. As shown in Figure 55, work zone throughput increased under both deployment scenarios, with AVs producing a 19% improvement and CAVs yielding an 18% increase. Despite the similar gains in throughput, notable differences were observed in mean travel speeds. As can be seen in Figure 56, AVs improved average speeds by 20%, whereas CAVs achieved a 70% increase. Speed was measured immediately downstream of the work zone using the same virtual detector employed for throughput analysis. This location reflects how efficiently traffic disperses after navigating the bottleneck. The substantial speed improvement in the CAV scenario, despite similar throughput, suggests more stable flow conditions and faster post-bottleneck recovery., In addition, the observed difference reflects the persistence of congestion and turbulence in non-connected environments. CAVs likely mitigated this effect through vehicle coordination, reduced reaction time variability, and anticipatory deceleration, which collectively helped suppress traffic shockwaves and improve dispersal efficiency. Following a similar trend, emissions metrics also showed substantial improvement, with CAVs outperforming AVs in reducing environmental impact. In a fully CAV environment, greenhouse gas (GHG) (as shown in Figure 57) emissions were reduced by 56%, while a fully AV environment achieved a 37% reduction. These reductions reflect improvements not only for the automated vehicle fleets but also for surrounding human-driven vehicles, due to smoother traffic flow and decreased idling. In parallel, air pollutant emissions (as shown in Figure 58) such as nitrogen oxides (NO_x) and particulate matter (PM) also declined, with reductions of 63% in the fully CAV scenario and 40% in the fully AV scenario. These findings reinforce the broader sustainability potential of CAV technology, which combines improvements in safety and mobility with meaningful reductions in environmental impact.

AV CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	775336 (0.00%)	782989 (0.99%)	822012 (6.02%)	845556 (9.06%)	860082 (10.93%)	864903 (11.55%)	883168 (13.91%)	847301 (9.28%)	832897 (7.42%)	700839 (-9.61%)	685435 (-11.60%)
10%	748725 (-3.43%)	779873 (0.59%)	807719 (4.18%)	786616 (1.45%)	798548 (2.99%)	749891 (-3.28%)	760388 (-1.93%)	661022 (-14.74%)	542062 (-30.09%)	529193 (-31.75%)	
20%	711124 (-8.28%)	719925 (-7.15%)	717418 (-7.47%)	706911 (-8.83%)	682790 (-11.94%)	664448 (-14.30%)	615841 (-20.57%)	490505 (-36.74%)	485679 (-37.36%)		
30%	641934 (-17.21%)	641557 (-17.25%)	633976 (-18.23%)	620112 (-20.02%)	593654 (-23.43%)	534198 (-31.10%)	456831 (-41.08%)	459043 (-40.79%)			
40%	584178 (-24.65%)	579712 (-25.23%)	553215 (-28.65%)	530277 (-31.61%)	481385 (-37.91%)	425667 (-45.10%)	362447 (-53.25%)				
50%	549916 (-29.07%)	539568 (-30.41%)	488389 (-37.01%)	475622 (-38.66%)	408422 (-47.32%)	373676 (-51.80%)					
60%	480501 (-38.03%)	476585 (-38.53%)	450986 (-41.83%)	403201 (-48.00%)	363745 (-53.09%)						
70%	435345 (-43.85%)	411695 (-46.90%)	382830 (-50.62%)	354869 (-54.23%)							
80%	384725 (-50.38%)	358972 (-53.70%)	331064 (-57.30%)								
90%	336432 (-56.61%)	331079 (-57.30%)									
100%	286152 (-63.09%)										

Figure 54. Critical Time-to-Collision Counts Under High Traffic Demand Scenario (Single Lane Drop)

AV CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	6159 (0.00%)	6269 (1.79%)	6414 (4.14%)	6473 (5.10%)	6619 (7.47%)	6772 (9.95%)	6930 (12.52%)	7045 (14.39%)	7182 (16.61%)	7270 (18.04%)	7315 (18.77%)
10%	6256 (1.57%)	6343 (2.99%)	6470 (5.05%)	6724 (9.17%)	6762 (9.79%)	6983 (13.38%)	7068 (14.76%)	7165 (16.33%)	7142 (15.96%)	7163 (16.30%)	
20%	6401 (3.93%)	6577 (6.79%)	6714 (9.01%)	6906 (12.13%)	7028 (14.11%)	7079 (14.94%)	7183 (16.63%)	7164 (16.32%)	7085 (15.03%)		
30%	6595 (7.08%)	6693 (8.67%)	6910 (12.19%)	7029 (14.13%)	7131 (15.78%)	7196 (16.84%)	7161 (16.27%)	7072 (14.82%)			
40%	6838 (11.02%)	6966 (13.10%)	7097 (15.23%)	7195 (16.82%)	7235 (17.47%)	7244 (17.62%)	7217 (17.18%)				
50%	6945 (12.76%)	7068 (14.76%)	7192 (16.77%)	7240 (17.55%)	7270 (18.04%)	7288 (18.33%)					
60%	7134 (15.83%)	7184 (16.64%)	7228 (17.36%)	7251 (17.73%)	7240 (17.55%)						
70%	7152 (16.12%)	7220 (17.23%)	7253 (17.76%)	7239 (17.54%)							
80%	7194 (16.80%)	7236 (17.49%)	7271 (18.05%)								
90%	7281 (18.22%)	7263 (17.92%)									
100%	7275 (18.12%)										

Figure 55. Work Zone Throughput (Veh/hr) Under High Traffic Demand Scenario (Single Lane Drop)

AV / CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	32.77 (0.00%)	32.95 (0.55%)	31.78 (-3.02%)	30.67 (-6.41%)	30.33 (-7.45%)	30.14 (-8.03%)	30.78 (-6.07%)	31.89 (-2.69%)	33.95 (3.60%)	37.9 (15.65%)	39.24 (19.74%)
10%	33.83 (3.23%)	32.32 (-1.37%)	31.52 (-3.81%)	31.49 (-3.91%)	31.56 (-3.69%)	31.86 (-2.78%)	30.84 (-5.89%)	36 (9.86%)	39.71 (21.18%)	39.66 (21.03%)	
20%	33.3 (1.62%)	33.1 (1.01%)	32.89 (0.37%)	32.66 (-0.34%)	32.44 (-1.01%)	32.78 (0.03%)	35.63 (8.73%)	40.05 (22.22%)	40 (22.06%)		
30%	35.48 (8.27%)	34.22 (4.42%)	34.28 (4.61%)	34.11 (4.09%)	34.6 (5.58%)	39.1 (19.32%)	40.83 (24.60%)	39.86 (21.64%)			
40%	37.36 (14.01%)	37.29 (13.79%)	37.87 (15.56%)	38.52 (17.55%)	42.61 (30.03%)	43.26 (32.01%)	42.33 (29.17%)				
50%	38.38 (17.12%)	39.01 (19.04%)	43.28 (32.07%)	44.31 (35.22%)	45.33 (38.33%)	45.15 (37.78%)					
60%	43.78 (33.60%)	43.37 (32.35%)	45.45 (38.69%)	45.93 (40.16%)	46.06 (40.56%)						
70%	45.75 (39.61%)	46.46 (41.78%)	47.23 (44.13%)	46.88 (43.06%)							
80%	49.61 (51.39%)	49.08 (49.77%)	50.33 (53.59%)								
90%	52.49 (60.18%)	52.71 (60.85%)									
100%	55.73 (70.06%)										

Figure 56. Mean Speed (MPH) Under High Traffic Demand Scenario (Single Lane Drop)

AV / CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	6252.57 (0.00%)	6074.92 (-2.84%)	5916.99 (-5.37%)	5722.55 (-8.48%)	5533.13 (-11.51%)	5261.27 (-15.85%)	5033.9 (-19.49%)	4590.07 (-26.59%)	4403.7 (-29.57%)	3976.17 (-36.41%)	3940.18 (-36.98%)
10%	6058.21 (-3.11%)	5883.24 (-5.91%)	5804.9 (-7.16%)	5471.64 (-12.49%)	5230.92 (-16.34%)	4829.71 (-22.76%)	4545.48 (-27.30%)	3987.71 (-36.22%)	3572.85 (-42.86%)	3458.76 (-44.68%)	
20%	5812.35 (-7.04%)	5606.05 (-10.34%)	5353.45 (-14.38%)	5078.42 (-18.78%)	4717.37 (-24.55%)	4403.97 (-29.57%)	4010.93 (-35.85%)	3538.09 (-43.41%)	3424.02 (-45.24%)		
30%	5414.49 (-13.40%)	5146.47 (-17.69%)	4838.81 (-22.61%)	4550.88 (-27.22%)	4190.03 (-32.99%)	3831.26 (-38.73%)	3538.92 (-43.40%)	3392.55 (-45.74%)			
40%	4874.5 (-22.04%)	4615.15 (-26.19%)	4243.6 (-32.13%)	3990.32 (-36.18%)	3650.66 (-41.61%)	3394.59 (-45.71%)	3230.21 (-48.34%)				
50%	4427.41 (-29.19%)	4179.59 (-33.15%)	3771.69 (-39.68%)	3529.89 (-43.54%)	3250.18 (-48.02%)	3084.3 (-50.67%)					
60%	3923.38 (-37.25%)	3711.43 (-40.64%)	3448.26 (-44.85%)	3183.08 (-49.09%)	3002.73 (-51.98%)						
70%	3535.83 (-43.45%)	3346.72 (-46.47%)	3140.82 (-49.77%)	3000.41 (-52.01%)							
80%	3299.71 (-47.23%)	3078.45 (-50.77%)	2908.2 (-53.49%)								
90%	2991.08 (-52.16%)	2877.89 (-53.97%)									
100%	2732.35 (-56.30%)										

Figure 57. Green House Gas Emission(kg) (CO2 and CO) Under High Traffic Demand Scenario (Single Lane Drop)

AV / CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	3.48 (0.00%)	3.36 (-3.45%)	3.27 (-6.03%)	3.15 (-9.48%)	3.02 (-13.22%)	2.85 (-18.10%)	2.71 (-22.13%)	2.43 (-30.17%)	2.33 (-33.05%)	2.08 (-40.23%)	2.08 (-40.23%)
10%	3.36 (-3.45%)	3.25 (-6.61%)	3.2 (-8.05%)	2.99 (-14.08%)	2.83 (-18.68%)	2.58 (-25.86%)	2.41 (-30.75%)	2.06 (-40.80%)	1.82 (-47.70%)	1.75 (-49.71%)	
20%	3.21 (-7.76%)	3.07 (-11.78%)	2.91 (-16.38%)	2.74 (-21.26%)	2.52 (-27.59%)	2.32 (-33.33%)	2.08 (-40.23%)	1.79 (-48.56%)	1.74 (-50.00%)		
30%	2.96 (-14.94%)	2.79 (-19.83%)	2.6 (-25.29%)	2.41 (-30.75%)	2.19 (-37.07%)	1.97 (-43.39%)	1.8 (-48.28%)	1.72 (-50.57%)			
40%	2.63 (-24.43%)	2.46 (-29.31%)	2.22 (-36.21%)	2.06 (-40.80%)	1.85 (-46.84%)	1.69 (-51.44%)	1.59 (-54.31%)				
50%	2.35 (-32.47%)	2.19 (-37.07%)	1.93 (-44.54%)	1.78 (-48.85%)	1.6 (-54.02%)	1.49 (-57.18%)					
60%	2.03 (-41.67%)	1.9 (-45.40%)	1.73 (-50.29%)	1.56 (-55.17%)	1.44 (-58.62%)						
70%	1.79 (-48.56%)	1.67 (-52.01%)	1.54 (-55.75%)	1.45 (-58.33%)							
80%	1.65 (-52.59%)	1.51 (-56.61%)	1.4 (-59.77%)								
90%	1.46 (-58.05%)	1.38 (-60.34%)									
100%	1.3 (-62.64%)										

Figure 58. Air Pollution (Kg) (NOx, HC, PMx) Under High Traffic Demand Scenario (Single Lane Drop)

A.5.2.2 Dual Lane Drops

A.5.2.2.1 Low Demand In this scenario, an additional lane was closed, resulting in a dual-lane drop work zone configuration. All other simulation parameters, including speed limits, traffic demand, and market penetration rates, remained consistent with the single-lane drop scenario. Even under low-demand conditions, the dual-lane drop configuration led to noticeably more complex traffic dynamics due to increased lane-changing activity and reduced roadway capacity. These intensified conditions allowed the benefits of CAVs to become more evident. Compared to both AVs and HDVs, CAVs demonstrated substantially superior performance across safety, mobility, and environmental metrics. As shown in Figure 59, safety performance, as measured by the Time-to-Collision (TTC) metric, showed a marked improvement in a fully CAV environment, with TTC decreasing by 71% relative to the fully human-driven baseline. By contrast, the fully AV environment experienced a 6% increase in critical TTC occurrences, suggesting a slight deterioration in safety under these conditions. This may be attributed to the limited adaptability of AVs in managing the increased turbulence associated with extensive lane closures. Mobility metrics also improved under automated and connected scenarios, as shown in Figure 60 and Figure 61. In a fully CAV environment, the mean speed increased by 78%, rising from 34 miles per hour to 60 miles per hour. Work zone throughput also increased, with improvements of 8.8% for CAVs and 8.6% for AVs, relative to the baseline. The modest throughput gains should be interpreted in the context of fixed demand levels. Since the number of vehicles in the network remained constant, improvements in speed and throughput reflect the ability of CAVs and AVs to reduce congestion and flow disruptions, rather than a true expansion of capacity. Environmental performance exhibited the most significant gains. In a fully AV environment, greenhouse gas (GHG) emissions, specifically carbon dioxide (CO_2) and carbon monoxide (CO), were reduced by 32% in Figure 62. In the fully CAV environment, emissions declined by 53%. Similarly, according to the Figure 63, air pollutant emissions such as nitrogen oxides (NO_x) and particulate matter (PM) were reduced by 34% in the AV scenario and by 59% in the CAV scenario. These substantial reductions are closely tied to smoother vehicle trajectories, fewer stop-and-go cycles, and improved flow stability. Although demand remained fixed, the enhanced operational efficiency of connected and automated vehicles contributed meaningfully to both emissions and air quality outcomes. These findings highlight the potential of CAVs not only to improve safety and mobility, but also to advance sustainability objectives, particularly in complex traffic conditions involving multiple lane closures.

AV / CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	478881 (0.00%)	447596 (-6.53%)	462403 (-3.44%)	472124 (-1.41%)	488153 (1.94%)	452986 (-5.41%)	480411 (0.32%)	506537 (5.78%)	550607 (14.98%)	504565 (5.36%)	508697 (6.23%)
10%	411907 (-13.99%)	411525 (-14.07%)	422877 (-11.69%)	389942 (-18.57%)	423652 (-11.53%)	404148 (-15.61%)	424262 (-11.41%)	413419 (-13.67%)	449627 (-6.11%)	425296 (-11.19%)	
20%	363647 (-24.06%)	357014 (-25.45%)	374484 (-21.80%)	366293 (-23.51%)	351137 (-26.68%)	364260 (-23.94%)	329294 (-31.24%)	344225 (-28.12%)	358279 (-25.18%)		
30%	315771 (-34.06%)	315771 (-34.06%)	288778 (-39.70%)	270718 (-43.47%)	259074 (-45.90%)	237986 (-50.30%)	264462 (-44.78%)	270400 (-43.54%)			
40%	272962 (-43.00%)	247856 (-48.24%)	251485 (-47.48%)	211244 (-55.89%)	177310 (-62.97%)	161009 (-66.38%)	145162 (-69.69%)				
50%	238192 (-50.26%)	213709 (-55.37%)	196804 (-58.90%)	160560 (-66.47%)	152672 (-68.12%)	121823 (-74.56%)					
60%	213408 (-55.44%)	183857 (-61.61%)	173923 (-63.68%)	150667 (-68.54%)	126879 (-73.51%)						
70%	186213 (-61.11%)	174829 (-63.49%)	157518 (-67.11%)	140462 (-70.67%)							
80%	163112 (-65.94%)	158956 (-66.81%)	142424 (-70.26%)								
90%	147323 (-69.24%)	140964 (-70.56%)									
100%	138424 (-71.09%)										

Figure 59. Critical Time-to-Collision Counts Under Low Traffic Demand Scenario (Dual Lane Drop)

AV / CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	4298 (0.00%)	4351 (1.23%)	4409 (2.58%)	4459 (3.75%)	4476 (4.14%)	4552 (5.91%)	4585 (6.68%)	4577 (6.49%)	4621 (7.52%)	4642 (8.00%)	4668 (8.61%)
10%	4397 (2.30%)	4448 (3.49%)	4495 (4.58%)	4574 (6.42%)	4574 (6.42%)	4605 (7.14%)	4596 (6.93%)	4595 (6.91%)	4584 (6.65%)	4599 (7.00%)	
20%	4525 (5.28%)	4554 (5.96%)	4577 (6.49%)	4591 (6.82%)	4638 (7.91%)	4628 (7.68%)	4623 (7.56%)	4608 (7.21%)	4590 (6.79%)		
30%	4584 (6.65%)	4611 (7.28%)	4646 (8.10%)	4661 (8.45%)	4657 (8.35%)	4621 (7.52%)	4603 (7.10%)	4627 (7.65%)			
40%	4633 (7.79%)	4670 (8.66%)	4668 (8.61%)	4677 (8.82%)	4677 (8.82%)	4677 (8.82%)	4677 (8.82%)				
50%	4674 (8.75%)	4675 (8.77%)	4677 (8.82%)	4677 (8.82%)	4677 (8.82%)	4677 (8.82%)					
60%	4677 (8.82%)	4675 (8.77%)	4678 (8.84%)	4677 (8.82%)	4677 (8.82%)						
70%	4677 (8.82%)	4677 (8.82%)	4676 (8.79%)	4677 (8.82%)							
80%	4679 (8.86%)	4679 (8.86%)	4678 (8.84%)								
90%	4680 (8.89%)	4680 (8.89%)									
100%	4676 (8.79%)										

Figure 60. Work Zone Throughput (Veh/hr) Under Low Traffic Demand Scenario (Dual Lane Drop)

CAV \ AV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	34.01 (0.00%)	37.19 (9.35%)	31.13 (-8.47%)	45.95 (35.11%)	31.78 (-6.56%)	33.1 (-2.68%)	32.27 (-5.12%)	31.32 (-7.91%)	31.41 (-7.64%)	41.19 (21.11%)	34.05 (0.12%)
10%	35.16 (3.38%)	37.54 (10.38%)	36.14 (6.26%)	43.12 (26.79%)	37.8 (11.14%)	41.96 (23.38%)	39.7 (16.73%)	40.31 (18.52%)	36.58 (7.56%)	40.34 (18.61%)	
20%	41.08 (20.79%)	42.94 (26.26%)	41.17 (21.05%)	39.65 (16.58%)	43.72 (28.55%)	40.18 (18.14%)	40.79 (19.94%)	40.78 (19.91%)	39.81 (17.05%)		
30%	44.66 (31.31%)	43.58 (28.14%)	47.81 (40.58%)	52.34 (53.90%)	52.69 (54.93%)	53.39 (56.98%)	43.05 (26.58%)	42.63 (25.35%)			
40%	48.29 (41.99%)	53.64 (57.72%)	53.42 (57.07%)	54.81 (61.16%)	53.94 (58.60%)	54.59 (60.51%)	54.27 (59.57%)				
50%	54.78 (61.07%)	55.36 (62.78%)	56.2 (65.25%)	56.76 (66.89%)	56.27 (65.45%)	55.51 (63.22%)					
60%	57.16 (68.07%)	57.99 (70.51%)	57.68 (69.60%)	56.18 (65.19%)	56.5 (66.13%)						
70%	58.68 (72.54%)	58.67 (72.51%)	58.4 (71.71%)	58.05 (70.69%)							
80%	58.96 (73.36%)	59.38 (74.60%)	58.53 (72.10%)								
90%	59.67 (75.45%)	59.53 (75.04%)									
100%	60.47 (77.80%)										

Figure 61. Mean Speed (MPH) Under Low Traffic Demand Scenario (Dual Lane Drop)

CAV \ AV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	3610.3 (0.00%)	3409 (-5.58%)	3333.6 (-7.66%)	3241.11 (-10.23%)	3096.43 (-14.23%)	2824.28 (-21.77%)	2790.92 (-22.70%)	2670.22 (-26.04%)	2645.35 (-26.73%)	2458.2 (-31.91%)	2450.92 (-32.11%)
10%	3405.47 (-5.67%)	3315.94 (-8.15%)	3189.09 (-11.67%)	2903.65 (-19.57%)	2860.33 (-20.77%)	2672.57 (-25.97%)	2535.53 (-29.77%)	2398.95 (-33.55%)	2363.57 (-34.53%)	2283.53 (-36.75%)	
20%	3208.71 (-11.12%)	3036.94 (-15.88%)	2958.54 (-18.05%)	2771.98 (-23.22%)	2542.28 (-29.58%)	2464.71 (-31.73%)	2279.59 (-36.86%)	2224.85 (-38.37%)	2123.42 (-41.18%)		
30%	2910.47 (-19.38%)	2756.07 (-23.66%)	2498.75 (-30.79%)	2310.66 (-36.00%)	2189.64 (-39.35%)	2055.29 (-43.07%)	2048.99 (-43.25%)	1962.32 (-45.65%)			
40%	2619.44 (-27.45%)	2420.58 (-32.95%)	2301.31 (-36.26%)	2067.86 (-42.72%)	1913.47 (-47.00%)	1783.02 (-50.61%)	1663.09 (-53.93%)				
50%	2370.76 (-34.33%)	2228.09 (-38.29%)	2060.48 (-42.93%)	1856.53 (-48.58%)	1775.48 (-50.82%)	1615.64 (-55.25%)					
60%	2166.38 (-39.99%)	1996.31 (-44.71%)	1902.36 (-47.31%)	1775.51 (-50.82%)	1671.63 (-53.70%)						
70%	2011.47 (-44.29%)	1909.11 (-47.12%)	1800.39 (-50.13%)	1717.93 (-52.42%)							
80%	1905.63 (-47.22%)	1827.46 (-49.38%)	1727.25 (-52.16%)								
90%	1785.59 (-50.54%)	1718.34 (-52.40%)									
100%	1707.95 (-52.69%)										

Figure 62. Green House Gas Emission(kg) (CO2 and CO) Under Low Traffic Demand Scenario (Dual Lane Drop)

CAV \ AV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	2.01 (0.00%)	1.88 (-6.47%)	1.83 (-8.96%)	1.77 (-11.94%)	1.68 (-16.42%)	1.51 (-24.88%)	1.49 (-25.87%)	1.42 (-29.35%)	1.42 (-29.35%)	1.31 (-34.83%)	1.32 (-34.33%)
10%	1.87 (-6.97%)	1.81 (-9.95%)	1.73 (-13.93%)	1.55 (-22.89%)	1.53 (-23.88%)	1.4 (-30.35%)	1.33 (-33.83%)	1.25 (-37.81%)	1.24 (-38.31%)	1.2 (-40.30%)	
20%	1.74 (-13.43%)	1.63 (-18.91%)	1.58 (-21.39%)	1.47 (-26.87%)	1.32 (-34.33%)	1.27 (-36.82%)	1.17 (-41.79%)	1.13 (-43.78%)	1.08 (-46.27%)		
30%	1.55 (-22.89%)	1.46 (-27.36%)	1.29 (-35.82%)	1.18 (-41.29%)	1.1 (-45.27%)	1.02 (-49.25%)	1.01 (-49.75%)	0.96 (-52.24%)			
40%	1.37 (-31.84%)	1.25 (-37.81%)	1.17 (-41.79%)	1.03 (-48.76%)	0.93 (-53.73%)	0.84 (-58.21%)	0.76 (-62.19%)				
50%	1.22 (-39.30%)	1.13 (-43.78%)	1.02 (-49.25%)	0.89 (-55.72%)	0.84 (-58.21%)	0.74 (-63.18%)					
60%	1.09 (-45.77%)	0.98 (-51.24%)	0.92 (-54.23%)	0.84 (-58.21%)	0.78 (-61.19%)						
70%	0.99 (-50.75%)	0.93 (-53.73%)	0.86 (-57.21%)	0.81 (-59.70%)							
80%	0.93 (-53.73%)	0.88 (-56.22%)	0.82 (-59.20%)								
90%	0.86 (-57.21%)	0.81 (-59.70%)									
100%	0.81 (-59.70%)										

Figure 63. Air Pollution (Kg) (NOx, HC, PMx) Under Low Traffic Demand Scenario (Dual Lane Drop)

A.5.2.2.2 Medium Demand The medium-demand scenario was defined as the median between the empirically observed high and low traffic volumes and corresponds to an input value of 6,014 vehicles per hour. All simulation parameters remained consistent with previous scenarios, including roadway geometry, vehicle behavior models, and market penetration rates. This scenario introduces a more congested traffic environment relative to the low-demand case, allowing for a more nuanced evaluation of vehicle technology performance under moderate stress conditions. The dual-lane drop configuration under medium demand further emphasized the distinctions between AVs and CAVs. In particular, safety outcomes diverged significantly across vehicle types. In the fully CAV environment, the Time-to-Collision (TTC) metric decreased by 63.4% as shown in Figure 64, indicating a substantial reduction in surrogate conflicts relative to the baseline. Conversely, in the fully AV scenario, TTC increased by 48%, suggesting a deterioration in safety performance. This adverse outcome may reflect the limitations of non-cooperative AV behavior in responding to increased merging activity and lateral disturbances common to dual-lane drop conditions at medium demand levels. Mobility performance also varied considerably as shown in Figure 65 and Figure 66. In a fully CAV environment, the mean speed nearly doubled, increasing by 96.2%, while work zone throughput improved by 31.3%. These results suggest that CAVs were highly effective in stabilizing flow, reducing shockwave formation, and enhancing post-bottleneck recovery. In contrast, the fully AV environment exhibited a 14% reduction in mean speed, though throughput still improved by 13.7%. This indicates that AVs were able to maintain vehicle throughput but did so at the expense of flow quality and travel efficiency. As with previous scenarios, it is important to note that these results were derived from a one-hour simulation period under fixed demand conditions. Throughput gains, therefore, reflect reduced congestion and improved flow reliability, rather than an increase in absolute capacity. Environmental performance metrics further reinforced the superior performance of CAVs. In the fully CAV environment, greenhouse gas (GHG) emissions were reduced by 51.3%, while the AV scenario achieved a more modest 12.1% reduction in Figure 67. Similarly, according to Figure 68, air pollutant emissions, including nitrogen oxides (NO_x) and particulate matter (PM), declined by 58.5% in the CAV scenario and by 9% in the AV scenario. These reductions can be attributed to smoother vehicle trajectories, reduced stop-and-go behavior, and fewer abrupt acceleration and deceleration events. Although demand remained constant, the enhanced operational efficiency of CAVs delivered significant environmental benefits. Overall, the medium-demand dual-lane drop scenario highlights the limitations of AVs in managing increasingly complex traffic conditions in the absence of vehicle-to-vehicle coordination. In contrast, CAVs consistently demonstrated superior performance across all evaluated dimensions, including safety, mobility, and environmental sustainability.

AV CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	750518 (0.00%)	781980 (4.19%)	812938 (8.32%)	854357 (13.84%)	884037 (17.79%)	930629 (24.00%)	986893 (31.49%)	1026073 (36.72%)	1071271 (42.74%)	1112834 (48.28%)	1107813 (47.61%)
10%	757916 (0.99%)	775694 (3.35%)	792775 (5.63%)	828171 (10.35%)	867238 (15.55%)	925897 (23.37%)	980563 (30.65%)	1006430 (34.10%)	1049656 (39.86%)	1049017 (39.77%)	
20%	727829 (-3.02%)	713138 (-4.98%)	729503 (-2.80%)	772702 (2.96%)	795579 (6.00%)	830647 (10.68%)	894873 (19.23%)	921209 (22.74%)	1016333 (35.42%)		
30%	645962 (-13.93%)	627692 (-16.37%)	646526 (-13.86%)	637960 (-15.00%)	634982 (-15.39%)	645460 (-14.00%)	707250 (-5.77%)	813701 (8.42%)			
40%	585486 (-21.99%)	567130 (-24.43%)	577129 (-23.10%)	555880 (-25.93%)	532415 (-29.06%)	520313 (-30.67%)	580737 (-22.62%)				
50%	542696 (-27.69%)	543636 (-27.57%)	530057 (-29.37%)	529776 (-29.41%)	517453 (-31.05%)	500943 (-33.25%)					
60%	508000 (-32.31%)	521369 (-30.53%)	510708 (-31.95%)	505341 (-32.67%)	503728 (-32.88%)						
70%	455246 (-39.34%)	476454 (-36.52%)	483084 (-35.63%)	473103 (-36.96%)							
80%	404417 (-46.11%)	409473 (-45.44%)	421099 (-43.89%)								
90%	335770 (-55.26%)	340130 (-54.68%)									
100%	274366 (-63.44%)										

Figure 64. Critical Time-to-Collision Counts Under Medium Traffic Demand Scenario (Dual Lane Drop)

AV CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	4530 (0.00%)	4611 (1.79%)	4666 (3.00%)	4645 (2.54%)	4771 (5.32%)	4817 (6.34%)	4810 (6.18%)	4854 (7.15%)	4954 (9.36%)	5011 (10.62%)	5150 (13.69%)
10%	4528 (-0.04%)	4641 (2.45%)	4772 (5.34%)	4814 (6.27%)	4928 (8.79%)	4931 (8.85%)	4953 (9.34%)	5078 (12.10%)	5113 (12.87%)	5203 (14.86%)	
20%	4571 (0.91%)	4743 (4.70%)	4852 (7.11%)	4891 (7.97%)	4967 (9.65%)	5087 (12.30%)	5100 (12.58%)	5180 (14.35%)	5227 (15.39%)		
30%	4795 (5.85%)	4997 (10.31%)	5092 (12.41%)	5199 (14.77%)	5301 (17.02%)	5364 (18.41%)	5347 (18.04%)	5326 (17.57%)			
40%	4893 (8.01%)	5128 (13.20%)	5286 (16.69%)	5390 (18.98%)	5553 (22.58%)	5623 (24.13%)	5402 (19.25%)				
50%	5100 (12.58%)	5256 (16.03%)	5475 (20.86%)	5575 (23.07%)	5675 (25.28%)	5726 (26.40%)					
60%	5315 (17.33%)	5444 (20.18%)	5578 (23.13%)	5722 (26.31%)	5752 (26.98%)						
70%	5539 (22.27%)	5605 (23.73%)	5727 (26.42%)	5745 (26.82%)							
80%	5652 (24.77%)	5710 (26.05%)	5719 (26.25%)								
90%	5817 (28.41%)	5829 (28.68%)									
100%	5947 (31.28%)										

Figure 65. Work Zone Throughput (Veh/hr) Under Medium Traffic Demand Scenario (Dual Lane Drop)

AV CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	28.07 (0.00%)	27.38 (-2.46%)	26.04 (-7.23%)	24.8 (-11.65%)	24.59 (-12.40%)	23.78 (-15.28%)	23.86 (-15.00%)	22.84 (-18.63%)	23.35 (-16.82%)	24.34 (-13.29%)	24.42 (-13.00%)
10%	27.36 (-2.53%)	27.12 (-3.38%)	26.61 (-5.20%)	25.97 (-7.48%)	25.21 (-10.19%)	23.91 (-14.82%)	23.61 (-15.89%)	24.01 (-14.46%)	24.28 (-13.50%)	25.23 (-10.12%)	
20%	28.76 (2.46%)	27.9 (-0.61%)	28.02 (-0.18%)	26.72 (-4.81%)	26.05 (-7.20%)	25.73 (-8.34%)	24.82 (-11.58%)	25.38 (-9.58%)	25.85 (-7.91%)		
30%	30.49 (8.62%)	30.8 (9.73%)	30.41 (8.34%)	30.25 (7.77%)	29.91 (6.56%)	30.02 (6.95%)	28.85 (2.78%)	29.54 (5.24%)			
40%	31.99 (13.97%)	32.03 (14.11%)	32.23 (14.82%)	32.34 (15.21%)	32.61 (16.17%)	34.41 (22.59%)	34.35 (22.37%)				
50%	33.85 (20.59%)	33.56 (19.56%)	34.29 (22.16%)	33.35 (18.81%)	33.85 (20.59%)	35.14 (25.19%)					
60%	36 (28.25%)	35.18 (25.33%)	35.92 (27.97%)	37 (31.81%)	37.46 (33.45%)						
70%	39.54 (40.86%)	38.38 (36.73%)	39.83 (41.90%)	40.04 (42.64%)							
80%	41.93 (49.38%)	42.71 (52.16%)	42.54 (51.55%)								
90%	47.92 (70.72%)	48.31 (72.11%)									
100%	55.1 (96.29%)										

Figure 66. Mean Speed (MPH) Under Medium Traffic Demand Scenario (Dual Lane Drop)

AV CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	4729.54 (0.00%)	4663.95 (-1.39%)	4582.67 (-3.11%)	4474.1 (-5.40%)	4388.17 (-7.22%)	4295.87 (-9.17%)	4243.14 (-10.28%)	4176.19 (-11.70%)	4093.33 (-13.45%)	4126.97 (-12.74%)	4158.03 (-12.08%)
10%	4727.54 (-0.04%)	4649.43 (-1.69%)	4539.28 (-4.02%)	4430.51 (-6.32%)	4322.23 (-8.61%)	4278.81 (-9.53%)	4212.07 (-10.94%)	4120.6 (-12.88%)	4063.42 (-14.08%)	4004.77 (-15.32%)	
20%	4650.84 (-1.66%)	4457.53 (-5.75%)	4274.9 (-9.61%)	4190.24 (-11.40%)	4014.73 (-15.11%)	3904.32 (-17.45%)	3908.82 (-17.35%)	3767.1 (-20.35%)	3874.82 (-18.07%)		
30%	4342.64 (-8.18%)	4085.57 (-13.62%)	3946.9 (-16.55%)	3666.89 (-22.47%)	3478.39 (-26.45%)	3302.06 (-30.18%)	3225.66 (-31.80%)	3354.35 (-29.08%)			
40%	3972.92 (-16.00%)	3788.24 (-19.90%)	3608.11 (-23.71%)	3381.45 (-28.50%)	3122.61 (-33.98%)	2907.57 (-38.52%)	2864.09 (-39.44%)				
50%	3699.59 (-21.78%)	3529.46 (-25.37%)	3316.41 (-29.88%)	3137.17 (-33.67%)	2920.28 (-38.25%)	2722.33 (-42.44%)					
60%	3400.06 (-28.11%)	3249.76 (-31.29%)	3021.27 (-36.12%)	2825.28 (-40.26%)	2669.78 (-43.55%)						
70%	2991.54 (-36.75%)	2911.59 (-38.44%)	2732.05 (-42.23%)	2570.52 (-45.65%)							
80%	2719.88 (-42.49%)	2592 (-45.20%)	2514.74 (-46.83%)								
90%	2495.34 (-47.24%)	2408.43 (-49.08%)									
100%	2302.7 (-51.31%)										

Figure 67. Green House Gas Emission(kg) (CO2 and CO) Under Medium Traffic Demand Scenario (Dual Lane Drop)

CAV \ AV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	2.7 (0.00%)	2.66 (-1.48%)	2.61 (-3.33%)	2.55 (-5.56%)	2.5 (-7.41%)	2.46 (-8.89%)	2.44 (-9.63%)	2.41 (-10.74%)	2.37 (-12.22%)	2.41 (-10.74%)	2.46 (-8.89%)
10%	2.69 (-0.37%)	2.64 (-2.22%)	2.57 (-4.81%)	2.51 (-7.04%)	2.45 (-9.26%)	2.44 (-9.63%)	2.41 (-10.74%)	2.36 (-12.59%)	2.34 (-13.33%)	2.33 (-13.70%)	
20%	2.64 (-2.22%)	2.51 (-7.04%)	2.4 (-11.11%)	2.34 (-13.33%)	2.24 (-17.04%)	2.18 (-19.26%)	2.2 (-18.52%)	2.13 (-21.11%)	2.24 (-17.04%)		
30%	2.43 (-10.00%)	2.26 (-16.30%)	2.18 (-19.26%)	2 (-25.93%)	1.88 (-30.37%)	1.77 (-34.44%)	1.74 (-35.56%)	1.87 (-30.74%)			
40%	2.2 (-18.52%)	2.08 (-22.96%)	1.96 (-27.41%)	1.82 (-32.59%)	1.65 (-38.89%)	1.52 (-43.70%)	1.52 (-43.70%)				
50%	2.03 (-24.81%)	1.92 (-28.89%)	1.78 (-34.07%)	1.66 (-38.52%)	1.52 (-43.70%)	1.4 (-48.15%)					
60%	1.84 (-31.85%)	1.74 (-35.56%)	1.59 (-41.11%)	1.46 (-45.93%)	1.36 (-49.63%)						
70%	1.58 (-41.48%)	1.53 (-43.33%)	1.41 (-47.78%)	1.3 (-51.85%)							
80%	1.4 (-48.15%)	1.32 (-51.11%)	1.26 (-53.33%)								
90%	1.25 (-53.70%)	1.19 (-55.93%)									
100%	1.12 (-58.52%)										

Figure 68. Air Pollution (Kg) (NOx, HC, PMx) Under Medium Traffic Demand Scenario (Dual Lane Drop)

A.5.2.2.3 High Demand The high-demand scenario represents the most congested traffic condition evaluated in this study and corresponds to the peak observed traffic volume of 7,352 vehicles per hour. As in previous scenarios, the dual-lane drop configuration was applied, and all other simulation parameters, including vehicle behavior models and market penetration rates, were held constant. Under these high-demand conditions, the distinctions between AVs and CAVs became even more pronounced. Safety outcomes, measured via the Time-to-Collision (TTC) metric, deteriorated substantially in the fully AV environment in Figure 69, where TTC increased by 50.52% compared to the human-driven baseline. This result highlights the limited capacity of non-cooperative AVs to manage complex interactions in heavily congested environments. In contrast, the fully CAV scenario yielded a 47.66% reduction in TTC, indicating a significant improvement in safety. However, a slight increase in conflict risk was observed at lower CAV market penetration rates (e.g., 10% and 20%), likely due to the behavioral discontinuity between connected and non-connected vehicles within the mixed traffic stream. Mobility metrics revealed a similar contrast in performance, as shown in Figure 70 and Figure 71. In the fully CAV environment, mean speed increased by 60.5%, reaching 42.33 miles per hour compared to the 26.70 mph baseline. In contrast, the fully AV scenario experienced a 10.26% reduction in mean speed, dropping to 23.96 mph. Work zone throughput also increased for both AVs and CAVs, with gains of 33.1% and 47.1%, respectively. These results indicate that while AVs were able to improve throughput, they did so at the expense of flow quality and vehicle spacing, resulting in degraded safety and mobility. CAVs, on the other hand, effectively coordinated movement across vehicles, improving both flow efficiency and operational stability. Environmental performance followed the same trend. According to Figure 72, Greenhouse gas (GHG) emissions, including carbon dioxide (CO_2) and carbon monoxide (CO), decreased by 10.34% in the AV scenario and by 42.63% in the CAV scenario. Similarly, air pollutant emissions such as nitrogen oxides (NO_x) and particulate matter (PM) declined by 6.75% in the AV environment and by 50% under full CAV deployment in Figure 73. These reductions are attributable to the smoother trajectories, reduced idling, and less aggressive acceleration behavior enabled by cooperative vehicle operation. Overall, the high-demand dual-lane drop scenario highlights the limitations of AV technology in the absence of connectivity and cooperation. While AVs provide moderate improvements in throughput and emissions, they struggle to manage complex safety interactions and exhibit limited gains in speed and flow reliability. In contrast, CAVs deliver consistent and substantial benefits across all performance metrics, underscoring their value in high-density, high-complexity freeway environments.

AV / CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	774531 (0.00%)	785623 (1.43%)	826765 (6.74%)	866926 (11.93%)	904970 (16.84%)	943162 (21.77%)	999077 (28.99%)	1047756 (35.28%)	1094554 (41.32%)	1154006 (48.99%)	1165482 (50.48%)
10%	768220 (-0.81%)	801628 (3.50%)	817279 (5.52%)	865780 (11.78%)	907535 (17.17%)	958354 (23.73%)	1008054 (30.15%)	1059876 (36.84%)	1107520 (42.99%)	1109484 (43.25%)	
20%	756151 (-2.37%)	787810 (1.71%)	810539 (4.65%)	857140 (10.67%)	900475 (16.26%)	955848 (23.41%)	1002589 (29.44%)	1044854 (34.90%)	1101616 (42.23%)		
30%	756844 (-2.28%)	758873 (-2.02%)	799810 (3.26%)	838683 (8.28%)	886108 (14.41%)	930245 (20.10%)	988706 (27.65%)	1060235 (36.89%)			
40%	750832 (-3.06%)	764037 (-1.35%)	804722 (3.90%)	801863 (3.53%)	848502 (9.55%)	907268 (17.14%)	972323 (25.54%)				
50%	741185 (-4.31%)	760522 (-1.81%)	758021 (-2.13%)	743436 (-4.01%)	753287 (-2.74%)	876086 (13.11%)					
60%	705567 (-8.90%)	712487 (-8.01%)	705700 (-8.89%)	676222 (-12.69%)	651738 (-15.85%)						
70%	633712 (-18.18%)	628684 (-18.83%)	619243 (-20.05%)	631977 (-18.41%)							
80%	544995 (-29.64%)	545431 (-29.58%)	552664 (-28.65%)								
90%	486932 (-37.13%)	488470 (-36.93%)									
100%	405401 (-47.66%)										

Figure 69. Critical Time-to-Collision Counts Under High Traffic Demand Scenario (Dual Lane Drop)

AV / CAV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	4497 (0.00%)	4640 (3.18%)	4694 (4.38%)	4723 (5.03%)	4758 (5.80%)	4852 (7.89%)	4807 (6.89%)	4878 (8.47%)	4979 (10.72%)	5032 (11.90%)	5129 (14.05%)
10%	4552 (1.22%)	4633 (3.02%)	4821 (7.20%)	4843 (7.69%)	4883 (8.58%)	4921 (9.43%)	5029 (11.83%)	5046 (12.21%)	5122 (13.90%)	5219 (16.06%)	
20%	4713 (4.80%)	4825 (7.29%)	5006 (11.32%)	5007 (11.34%)	5087 (13.12%)	5141 (14.32%)	5205 (15.74%)	5258 (16.92%)	5327 (18.46%)		
30%	4810 (6.96%)	5198 (15.59%)	5271 (17.21%)	5412 (20.35%)	5425 (20.64%)	5461 (21.44%)	5512 (22.57%)	5465 (21.53%)			
40%	5100 (13.41%)	5393 (19.92%)	5500 (22.30%)	5653 (25.71%)	5688 (26.48%)	5792 (28.80%)	5812 (29.24%)				
50%	5246 (16.66%)	5382 (19.68%)	5631 (25.22%)	5889 (30.95%)	6015 (33.76%)	5935 (31.98%)					
60%	5440 (20.97%)	5598 (24.48%)	5908 (31.38%)	6278 (39.60%)	6420 (42.76%)						
70%	5851 (30.11%)	6096 (35.56%)	6246 (38.89%)	6492 (44.36%)							
80%	6201 (37.89%)	6339 (40.96%)	6525 (45.10%)								
90%	6353 (41.27%)	6486 (44.23%)									
100%	6572 (46.14%)										

Figure 70. Work Zone Throughput (Veh/hr) Under High Traffic Demand Scenario (Dual Lane Drop)

CAV \ AV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	26.7 (0.00%)	27.16 (1.72%)	26.92 (0.82%)	25.47 (-4.61%)	24.56 (-8.01%)	23.86 (-10.64%)	22.41 (-16.07%)	22.73 (-14.87%)	22.59 (-15.39%)	24.22 (-9.29%)	23.96 (-10.26%)
10%	26.88 (0.67%)	26.4 (-1.12%)	25.9 (-3.00%)	24.94 (-6.59%)	24.65 (-7.68%)	23.7 (-11.24%)	23.39 (-12.40%)	22.73 (-14.87%)	23.69 (-11.27%)	24.24 (-9.21%)	
20%	28.79 (7.83%)	27.84 (4.27%)	27.19 (1.84%)	25.24 (-5.47%)	24.95 (-6.55%)	23.57 (-11.72%)	23.36 (-12.51%)	25.04 (-6.22%)	25.31 (-5.21%)		
30%	29.28 (9.66%)	29.54 (10.64%)	28.36 (6.22%)	26.83 (0.49%)	25.74 (-3.60%)	25.54 (-4.34%)	25.13 (-5.88%)	25.93 (-2.88%)			
40%	30.79 (15.32%)	29.99 (12.32%)	28.96 (8.46%)	28.12 (5.32%)	26.98 (1.05%)	26.36 (-1.27%)	27.69 (3.71%)				
50%	30.72 (15.06%)	30.95 (15.92%)	30.01 (12.40%)	29.39 (10.07%)	28.9 (8.24%)	28.59 (7.08%)					
60%	32.61 (22.13%)	31.47 (17.87%)	32.59 (22.06%)	32.18 (20.52%)	30.81 (15.39%)						
70%	34.55 (29.40%)	35.2 (31.84%)	33.91 (27.00%)	33.59 (25.81%)							
80%	37.31 (39.74%)	37.9 (41.95%)	37.41 (40.11%)								
90%	39.45 (47.75%)	39.36 (47.42%)									
100%	42.33 (58.54%)										

Figure 71. Mean Speed (MPH) Under High Traffic Demand Scenario (Dual Lane Drop)

CAV \ AV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	4795.9 (0.00%)	4716.11 (-1.66%)	4677.08 (-2.48%)	4552.35 (-5.08%)	4461.21 (-6.98%)	4362.56 (-9.04%)	4302.04 (-10.30%)	4265.45 (-11.06%)	4236.64 (-11.66%)	4242.46 (-11.54%)	4299.93 (-10.34%)
10%	4798.49 (0.05%)	4732.85 (-1.31%)	4666.75 (-2.69%)	4580.09 (-4.50%)	4470.41 (-6.79%)	4390.37 (-8.46%)	4311.88 (-10.09%)	4291.26 (-10.52%)	4221.62 (-11.97%)	4166.87 (-13.12%)	
20%	4842.4 (0.97%)	4761.34 (-0.72%)	4670.82 (-2.61%)	4565.97 (-4.79%)	4475.57 (-6.68%)	4401.96 (-8.21%)	4285.7 (-10.64%)	4200.4 (-12.42%)	4157.57 (-13.31%)		
30%	4827.21 (0.65%)	4748.23 (-0.99%)	4679.11 (-2.44%)	4557.87 (-4.96%)	4466.06 (-6.88%)	4293.36 (-10.48%)	4219.18 (-12.03%)	4081.35 (-14.90%)			
40%	4852.85 (1.19%)	4764.6 (-0.65%)	4644.07 (-3.17%)	4424.48 (-7.74%)	4221.49 (-11.98%)	4154.82 (-13.37%)	3996.33 (-16.67%)				
50%	4695.05 (-2.10%)	4536.55 (-5.41%)	4316.62 (-9.99%)	3954.48 (-17.54%)	3690.81 (-23.04%)	3729.29 (-22.24%)					
60%	4270.79 (-10.95%)	4099.29 (-14.53%)	3836.74 (-20.00%)	3471.98 (-27.61%)	3161.23 (-34.08%)						
70%	3717.98 (-22.48%)	3559.78 (-25.77%)	3309.75 (-30.99%)	3111.54 (-35.12%)							
80%	3333.26 (-30.50%)	3118 (-34.99%)	2995.39 (-37.54%)								
90%	3004.83 (-37.35%)	2918.11 (-39.15%)									
100%	2751.33 (-42.63%)										

Figure 72. Green House Gas Emission(kg) (CO2 and CO) Under High Traffic Demand Scenario (Dual Lane Drop)

CAV \ AV	0%	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
0%	2.74 (0.00%)	2.69 (-1.82%)	2.66 (-2.92%)	2.6 (-5.11%)	2.55 (-6.93%)	2.49 (-9.12%)	2.48 (-9.49%)	2.47 (-9.85%)	2.46 (-10.22%)	2.49 (-9.12%)	2.56 (-6.57%)
10%	2.74 (0.00%)	2.7 (-1.46%)	2.64 (-3.65%)	2.6 (-5.11%)	2.54 (-7.30%)	2.5 (-8.76%)	2.47 (-9.85%)	2.48 (-9.49%)	2.45 (-10.58%)	2.45 (-10.58%)	
20%	2.75 (0.36%)	2.7 (-1.46%)	2.63 (-4.01%)	2.58 (-5.84%)	2.53 (-7.66%)	2.5 (-8.76%)	2.44 (-10.95%)	2.41 (-12.04%)	2.42 (-11.68%)		
30%	2.73 (-0.36%)	2.66 (-2.92%)	2.62 (-4.38%)	2.54 (-7.30%)	2.5 (-8.76%)	2.41 (-12.04%)	2.38 (-13.14%)	2.34 (-14.60%)			
40%	2.73 (-0.36%)	2.66 (-2.92%)	2.59 (-5.47%)	2.44 (-10.95%)	2.33 (-14.96%)	2.31 (-15.69%)	2.25 (-17.88%)				
50%	2.63 (-4.01%)	2.53 (-7.66%)	2.37 (-13.50%)	2.14 (-21.90%)	1.98 (-27.74%)	2.04 (-25.55%)					
60%	2.37 (-13.50%)	2.25 (-17.88%)	2.07 (-24.45%)	1.83 (-33.21%)	1.63 (-40.51%)						
70%	2.02 (-26.28%)	1.9 (-30.66%)	1.73 (-36.86%)	1.59 (-41.97%)							
80%	1.76 (-35.77%)	1.61 (-41.24%)	1.53 (-44.16%)								
90%	1.54 (-43.80%)	1.48 (-45.99%)									
100%	1.37 (-50.00%)										

Figure 73. Air Pollution (Kg) (NOx, HC, PMx) Under High Traffic Demand Scenario (Dual Lane Drop)

A.5.3 Summary This chapter presents the simulation results for freeway work zone scenarios involving both single-lane and dual-lane drops under varying traffic demand levels. The analysis evaluates the performance of AVs and CAVs in terms of safety, mobility, and environmental impact. Across all scenarios, CAVs consistently showed more favorable outcomes, particularly as work zone conditions became more constrained and traffic demand increased. While AVs contributed to improvements in certain areas, they were less effective in maintaining flow stability and managing conflicts in more complex environments. These findings underscore the growing relevance of vehicle connectivity in supporting safe and efficient operations within freeway work zones.

A.6 Summary and Conclusions

A.6.1 Introduction Connected and Automated Vehicle (CAV) technologies integrate the capabilities of connected vehicles (CV) and automated vehicles (AV), offering a powerful combination of communication and autonomous driving features. By leveraging the strengths of both technologies, CAVs have the potential to significantly revolutionize transportation systems by improving safety, enhancing mobility, and contributing to environmental sustainability goals. However, due to the increasing demand for pavement maintenance and upgrades to preserve an acceptable level of service, work zone activities will remain a critical and frequent necessity. Work zones, in turn, can severely impact roadway safety, reduce operational efficiency and capacity, and contribute to negative environmental consequences both locally and globally. Addressing these work zone-induced challenges demands substantial investments in cutting-edge technologies and intelligent transportation systems to mitigate their adverse effects. As CAVs increasingly become part of the transportation ecosystem, their interaction with work zones becomes inevitable. Understanding and optimizing this interaction is essential, as CAVs have the potential to improve traffic flow and safety within these disruptive zones. Given the expected rise in CAV market penetration, evaluating their role in mitigating work zone challenges is a timely and necessary area of research with significant implications for future transportation planning and policy. The main objective of this project was to evaluate the potential impact of Connected and Automated Vehicles (CAVs) on work zone safety, operational efficiency, and environmental outcomes, across different levels of sensitivity related to traffic demand and varying vehicle compositions. Using the Simulation of Urban Mobility (SUMO) microsimulation platform, a representative freeway segment prone to work zone activity was identified through the Caltrans Performance Measurement System (PeMS) database. To ensure realistic modeling, various metaheuristic algorithms were employed to calibrate car-following parameters based on observed traffic behavior under human-driven conditions. Following calibration, simulations were conducted under multiple scenarios featuring different market penetration rates of (AVs) and CAVs and work zone configurations. Simulation results were analyzed in detail to understand the effects on traffic flow, safety, and emissions. Overall, the findings of this study provide valuable insights for traffic engineers, planners, and stakeholders by illustrating how varying levels CAV adoption could influence freeway work zone performance and contribute toward achieving broader safety, mobility, and environmental sustainability goals. These insights can ultimately support improved traffic management strategies in work zone settings.

A.6.2 Summary and Conclusions Through a comprehensive review of the current state-of-the-art and state-of-the-practice of CAV technologies around work zones, various methodological approaches to integrated CAV technologies (mostly CV and AV technologies) in work zone environment are summarized. Simulation-based method has been widely used in CAV related studies. Compared to other approaches, simulation-based method is imperative for practical decision making in transportation planning and operations. To conduct analysis using microsimulation models, potential scenarios need to be selected. Given the challenges associated with obtaining comprehensive work zone traffic data, this study utilized the Caltrans Performance Measurement System (PeMS) as the primary data source. PeMS is a web-based platform that provides users with real-time and historical traffic data, including speed, flow, capacity, and delay metrics. By leveraging PeMS, researchers can access detailed information on freeway segments, identify congestion bottlenecks, evaluate freeway performance, and inform operational decision-making. In this study, a four-lane (one direction) freeway segment was selected from PeMS. The site was chosen based on its minimal ramp interference and moderate baseline congestion, providing a stable scenario before simulating lane drops to introduce work zone conditions. Traffic simulation serves as a fundamental tool in transportation planning due to its cost-effectiveness, scalability, and proven ability to replicate complex traffic dynamics. In this study, the microscopic traffic simulation software Simulation of Urban Mobility (SUMO) was employed to model traffic operations throughout the analysis. To accurately replicate the real-world traffic flow and speed patterns observed in the PeMS data, three metaheuristic algorithms were implemented to calibrate the simulation: Genetic Algorithm (GA), Particle Swarm Optimization (PSO), and Simulated Annealing (SA). Each algorithm was independently evaluated with the objective of minimizing the discrepancy between observed traffic conditions and simulated outputs. Although the algorithms are inherently different in their optimization approaches, the study prioritized obtaining the most accurate calibration results rather than comparing algorithmic performance. Among the three, the PSO algorithm achieved the best calibration results, yielding an accuracy of 11.38%, which is notably better than the default parameters (19.2%). After completing the calibration, single- and double-lane drop scenarios were introduced into the freeway segment. For each scenario, different market penetration rates of AVs and CAVs were tested under varying traffic demand levels. These demand levels included low traffic (observed from the collected data), medium traffic (defined as the median value between low and high demand), and high traffic (selected from peak observed values). Different mixtures of vehicle types were introduced, and key performance metrics related to safety (Time-to-Collision, TTC), mobility (work zone throughput and mean speed), and environmental impact (air pollution and greenhouse gas emissions) were collected for each scenario. The findings suggest that the impact of CAVs is often minimal under low traffic intensity, particularly in relation to lane closures and demand levels. However, as traffic conditions become more intense, the benefits of CAV deployment become increasingly evident. Connected and Autonomous Vehicles (CAVs) consistently demonstrated superior performance across safety, mobility, and environmental metrics compared to Human-Driven Vehicles (HDVs) and standalone Autonomous Vehicles (AVs) in multiple freeway work zone scenarios. Under low-demand conditions, the benefits of CAVs were relatively modest, given the absence of significant congestion. However, as traffic demand increased, CAVs substantially reduced surrogate crash conflicts, improved mean speeds, and decreased greenhouse gas emissions and air pollution metrics. For instance, under high-demand single-lane drop scenarios, CAVs reduced critical Time-to-Collision (TTC) events by 63%, increased downstream mean speeds by up to 70%, and achieved a 56% reduction in greenhouse gas emissions. These improvements are largely attributed to CAVs' ability to coordinate vehicle movements, smooth traffic flows, and mitigate shockwave effects, advantages that AVs without connectivity could not replicate at the same level. Under more complex dual-lane drop conditions, the advantages of CAVs became even more pronounced. While AVs sometimes worsened safety by failing to adapt to high merging activity, CAVs effectively stabilized flow, doubled mean speeds, and provided substantial environmental benefits, including up to a 59% reduction in air pollutant emissions under high-demand conditions. Even in highly congested environments, CAVs maintained operational stability and reduced crash risk, emphasizing that connectivity is crucial for managing complex freeway scenarios. Overall, the study clearly indicates that while AVs alone offer limited and sometimes inconsistent benefits, the integration of connectivity through CAV systems yields significant improvements across all critical dimensions, making CAVs essential for future freeway traffic management.

A.6.3 Direction for Future Research While this study offers several useful findings, there are areas for improvement that future research could address. The work zones evaluated in this study were limited to basic freeway segments. Future studies could expand the scope to more complex scenarios such as merging areas, diverging segments, or freeway weaving sections. Additionally, the calibration process in this study relied on metaheuristic approaches, which, while effective, could be further enhanced. Future research could incorporate artificial intelligence-based optimization techniques to improve calibration accuracy and robustness. Extending the calibration process to include other car-following models would also provide a more comprehensive analysis. Beyond freeways, future studies could investigate the impact of CAVs on work zones along arterial roadways, where different traffic dynamics and control measures may present unique challenges and opportunities.

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