RESEARCH & DEVELOPMENT

Operational and Economic Impacts of Connected and Autonomous Vehicles

Srinivas S. Pulugurtha, Ph.D., P.E., F.ASCE, The University of North Carolina at Charlotte UNC Charlotte)

Hardik Gajera, M.Tech., UNC Charlotte

Ninad Gore, Ph.D., UNC Charlotte

Amirhossein Ghasemi, Ph.D., UNC Charlotte

Raghavan Srinivasan, Ph.D., University of North Carolina (UNC) Chapel Hill

Nitesh R. Shah , Ph.D., UNC Chapel Hill

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16. Abstract

The focus of this study is to quantify the effect of connected and autonomous vehicles (CAVs) on traffic operations, safety, and economy. A literature review was conducted to identify suitable analysis techniques and driving behavior parameters to mimic different levels of CAVs. Two road networks with freeways and arterial streets in Charlotte and Raleigh were developed in a microsimulation software and calibrated. Thirteen scenarios with varying penetration for different levels of CAVs were generated. The parameters such as travel time variation, the percentage reduction in travel time and delay, and buffer time were used to quantify the operational benefits. Time-to-collision and conflict types were identified from vehicular trajectories, and crashes were predicted for each scenario using an extreme value theory-based peak-over threshold approach. The economic impact is quantified by identifying the cost of buffer time per vehicle per mile and crash cost per mile. The results revealed that an increase in the penetration of CAVs would significantly reduce travel times, delays, buffer times, and the number of crashes. The impact of the reduction in buffer time and crashes on the economy is quantified, and values for the crash cost and buffer time per vehicle per mile were recommended for forecasting statewide impacts.

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Executive Summary

Connected and autonomous vehicles (CAVs) have drawn the attention of researchers in transportation engineering and other disciplines to investigate their potential impact on mobility and safety. The CAVs are expected to integrate into the transportation system through six levels of automation varying from Level 0 (no automation) to Level 5 (fully automated vehicles). Each level of CAV has varying capabilities regarding automation and connectivity with other vehicles and infrastructure. Therefore, the penetration and benefits of these vehicles in terms of operations, safety, and economy could vary significantly over years.

Although different levels of CAVs are expected to positively affect the existing transportation system, CAVs and human-driven vehicles (HDVs) are expected to coexist for a considerable amount of time. Therefore, a mix of vehicles with varying levels of automation and HDVs would create heterogeneity and uncertainty in vehicle-to-vehicle interactions. Quantifying the effect of mixed traffic at a micro-level would provide a better idea about the effect of increasing penetration of CAVs on operations, safety, and the economy of the transportation system. Researching, modeling, and forecasting the operational and economic impacts of varying penetrations of CAVs over time is needed to proactively plan, design, and operate the transportation infrastructure of North Carolina. The objectives of the proposed research are 1) to evaluate the operational and safety performance of the transportation network at various penetration rates of CAVs, and 2) to research and assess the impact of CAVs on the economy.

A comprehensive literature review was conducted to identify the best practices and methods for quantifying the effect of CAVs on operations, safety, and the economy. The microsimulation approach was identified as the most suitable technique considering the unavailability of real-world CAVs data. Amongst various microsimulation tools, PTV Vissim is widely used in the literature because of its flexibility in modeling CAVs. Therefore, PTV Vissim is used in this study. Further, to mimic the behavior of different levels of CAVs, driving behavior parameters for each level of CAV and the forecasted penetration of various levels of CAVs were identified from the existing literature.

Two networks, one in Charlotte and the other in Raleigh, were selected for the study. The network selected in the present study has varying road functional classes (freeways and arterial streets), speed limits (35 mph to 65mph), and intersection types (signalized and staggered). The microsimulation models with the freeway corridor and arterial streets in the Charlotte area and a freeway corridor in the Raleigh area were developed. Details such as road geometry, desired speed distributions, traffic volume composition and turning proportions, vehicle routes, signal plans, and phasing were incorporated into the network using real-world data collected from multiple sources.

An iterative method was adopted to calibrate the driving behavior parameters for the base traffic condition. The driving behavior parameters were calibrated by minimizing the error between the observed and simulated travel times. The driving behavior parameters were modified to model varying levels of CAVs. Level 1, Level 2, and Level 3 CAVs were modeled using the driving behavior parameters reported in the literature. On the other hand, the driving behavior parameters defined in the CoExist model were used to model Level 4 and Level 5 CAVs.

The forecasted penetration rates for varying levels of CAVs were defined based on the literature. A total of 13 scenarios were generated with varying penetration of different levels of CAVs. The scenarios were tested for three traffic volumes, including existing peak hour traffic volumes, off-peak traffic volumes (half of the peak hour demand), and forecasted peak traffic volumes for 2030.

The variation in travel times, the percentage reduction in travel time and delay per vehicle, and buffer time were considered as performance measures for quantifying the operational effects of CAVs. The vehicle trajectories were extracted from microsimulation models to quantify the safety benefits. The trajectories were processed using the surrogate safety assessment model (SSAM) to compute the time-to-collision for each conflict and identify conflict types (rear-end, lane change, and crossing). From the conflict data, crashes were estimated for each scenario using an extreme value theory-based peak-over threshold approach. Further, to quantify the economic benefits of CAV penetration, the cost of buffer time per vehicle per mile and crash cost per mile were estimated for freeways and arterial streets.

The operational analysis showed that with increasing penetration of various levels of CAVs, travel time per vehicle on freeways would decrease by 9.72% compared to the base traffic scenario. A 29.2% reduction in travel time per vehicle was noted on arterial streets. The results indicate a negligible reduction in travel time with increasing penetration of Level 1 and Level 2 CAVs. However, with increasing penetration of Level 3, Level 4, and Level 5 CAVs, travel time per vehicle decreases significantly. The delay per vehicle is estimated to be reduced by up to 40% and 40.7% on freeways and arterial streets, respectively. The analysis of buffer time revealed a reduction in buffer time with increased penetration of CAVs.

The safety benefits of CAVs are estimated to increase significantly with increasing penetration of CAVs. The safety benefits of CAVs on freeways increased when HDVs were replaced by Level 3 and higher level CAVs. Similarly, the number of crashes reduced significantly on the arterial streets once Level 3 CAVs begin to penetrate the transportation network. The number of rear-end and lane change crashes on freeways is estimated to decrease from 2.327 and 5.797 in the base scenario to 0.023 and 0.523 when the penetration of Level 5 CAVs is ~100%. Similarly, rear-end and lane change crashes on arterial streets is estimated to decrease from 1.646 and 5.411 in the base scenario to 0.025 and 0.0272 when the penetration of Level 5 CAVs is ~100%.

The increasing penetration of CAVs (higher penetration of Level 3, Level 4, and Level 5 CAVs) is estimated to have significant economic benefits in buffer time and crash cost savings. The cost of buffer time per vehicle per mile for freeways in North Carolina is estimated to be reduced from $0.055 in the base scenario to 0.043 in the scenario with ~100% penetration of Level 5 CAVs. It is estimated to reduce from $1.41 to $0.50 on arterial streets. On freeways, the crash cost per mile for rear-end and lane change crashes is estimated to reduce from $27,087 and $1,68,697 in the base scenario to $268 and $15,220 in the scenario with ~100% penetration of Level 5 CAV. Similarly, on arterials, the cost of rear-end and lane change crashes per mile is estimated to be reduced from $45,941 and $3,77,558 in the base scenario to $698 and $18,797 in the scenario with ~100% penetration of Level 5 CAV.

Overall, the CAVs will benefit the transportation system of North Carolina in terms of operations, safety, and economy. The estimated values of crash cost per mile for freeways and arterials are useful to forecast the total crash cost under varying penetration of different levels of CAVs. Further, the recommended cost of buffer time per vehicle per mile corresponding to different penetration scenarios would assist practitioners in quantifying the economic benefits of buffer time savings for freeways and arterial streets.

The methodology highlighted in the study serves as a framework for analyzing the operational, safety, and economic effects of a heterogeneous traffic flow. It could also be used to project benefits under scenarios with varying penetration of CAVs in the future.

1. Introduction

Advancements in vehicle technology are expected to change existing traffic systems fundamentally. Connected and autonomous vehicles (CAVs) have recently drawn much attention from researchers in transportation engineering and other disciplines, particularly investigating the potential benefits the CAVs would bring regarding mobility and safety. Through the information obtained using onboard sensors and other roadside units (RSU), CAVs are expected to mitigate human errors while performing driving-related tasks, thereby reducing traffic-related crashes and fatalities. The global market for CAVs in 2019 was estimated to be $55 billion, and it is projected to reach $556 billion by 2026, with a compound annual growth rate of up to 40% (Correa, 2019). According to S&P Global Ratings, CAVs are expected to account for up to 50% of the market share in the United States by 2040 (Leitzinger, 2019).

As the demand for CAVs increases over time, it will undoubtedly impact the operational performance and economy of transportation networks. When considering various micro- and macro-level factors, such as travel demand, congestion cost, traffic safety, employment rate of the transportation sector, energy market, insurance cost, and emissions, the operational and economic impacts of CAVs can be either positive or negative.

According to SAE International, CAVs will integrate into the existing transportation system in six different levels of automation (SAE, 2019). The levels of automation defined by SAE vary from Level 0 (no driving automation) to Level 5 (full driving automation). With the expected rise in the penetration rates of CAVs equipped with wireless communication, there will be a growing demand for data-based models to analyze heterogeneous traffic networks. Heterogeneity in this context stems from differences in human behavior, vehicle characteristics, and the level of autonomy. Analyzing the headway characteristics of heterogeneous traffic flow (i.e., a mix of CAVs and human-driven vehicles (HDVs)) can be complex. An HDV typically maintains a two-second headway when following another HDV. However, this may vary due to varying types of drivers (timid, conservative, cautious, and aggressive) and their driving behavior. When following CAVs, the behavior of the HDVs may differ due to different expectations of vehicle dynamics. Similarly, when a CAV follows an HDV, the lack of communication can lead to different responses compared to following another CAV. The car-following and lane-changing behavior of heterogeneous traffic networks presents inherent challenges to analyzing their impact on mobility and safety, which differ depending on the penetration of varying levels of CAVs, the types of roads, including freeways, arterial streets, collector roads, and local roads, traffic flow conditions, and traffic control and its characteristics.

Current efforts in this field have primarily focused on developing analytical and simulation models for CAVs and investigating the effect of CAVs on road capacity, intersection performance, travel time, and safety. Although these models provide valuable insights, they often rely on restrictive assumptions about the behavior of both HDVs and CAVs. Another crucial factor that significantly influences a road's capacity but has received less attention is the employment of appropriate operational and traffic control strategies. For example, different platooning intensities, even with the same heterogeneity level, can significantly affect operational and safety performance. CAVs can operate with less spacing and headway compared to HDVs. Therefore, it is crucial to understand how CAVs can enhance the mobility and safety of a traffic network under different penetration rates and operating scenarios.

The increased use of CAVs may replace jobs humans hold, such as taxi services, ride-sharing platforms (e.g., Uber), delivery services, transit system operators, and trucking operators. This shift could result in a substantial increase in the unemployment rate within the transportation sector. On the other hand, the reduced cost of services due to increased CAV usage is expected to expand mobility options, particularly for teenagers, older people, and people with disabilities. Consequently, this could lead to higher travel demand, increasing congestion and emissions. Evaluating these impacts can be achieved through microscopic simulation models by testing varying traffic demand scenarios and identifying the effect of penetration of CAVs on operations, safety, and the economy.

One potential advantage of using CAVs is the elimination of risks associated with diverse factors like driver behavior, vehicle characteristics, and road conditions. This could lead to a uniform and non-diverse personal auto insurance system for vehicle users, and reduced insurance costs due to fewer crashes. Consequently, this would result in reduced revenues and profits for insurance companies. Considering the varying automation in different levels of CAVs, it is necessary to identify the effect of penetrations of varying levels of CAVs on the operation and the safety of the transportation system. While the number of crashes is anticipated to decrease with the increasing penetration rate of CAVs, the specific impacts are not yet fully understood. In addition, the safety benefits may vary due to the mix of varying levels of CAVs and HDVs. Therefore, exploring microscopic simulation models and other analytical approaches to research and address this question is crucial.

The economic benefits of improved safety could be substantial, given that the estimated costs of road fatalities, injuries, and property damage exceed $339 billion in 2019 (Blincoe et al., 2023). However, current policies must be revised to determine liability in the event of a crash involving CAVs. As CAVs could maintain a relatively lesser distance from other vehicles than HDVs, a stable traffic flow resulting in stable travel times is expected. These stable travel times would possibly reduce buffer time and increase travel time savings, significantly influencing the economic cost associated with a reduction in travel time and buffer time. The economic benefits associated with the reduction in travel times or buffer times would depend on the penetration of varying levels of CAVs.

To comprehensively assess the operational performance (mobility and safety) of transportation networks under different penetration rates of CAVs, it is imperative to develop heterogeneous microscopic simulation models. These models will provide valuable insights into the operational and safety benefits of CAVs and their associated economic impacts, such as costs related to operations and safety at various levels of CAV penetration. Research, modeling, and forecasting the operational and economic impacts caused by penetrations of varying levels of CAVs are essential for proactive planning, design, and operation of transportation networks in North Carolina.

The objectives of this research, therefore, are:

- to evaluate the operational and safety performance of the transportation network at various penetration rates of CAVs, and,
- to research and assess the impact of CAVs on the economy.

1.2. Practical and Scientific Contributions of the Study

The practical and scientific contributions of the study are listed next.

- This study systematically quantifies how the penetration of varying levels of CAVs would influence the operational performance of different road functional classes.
- This study, using the extreme value theory (EVT)-based peak-over threshold (POT) approach, explains how crash risk and number of crashes would vary with the penetration of varying levels of CAVs.
- This study quantifies the economic impact associated with the operational and safety benefits of CAVs.
- The study provides a simple yet comprehensive framework for evaluating the effect of CAVs on operations, safety, and economy. The proposed framework can be used to project the statewide impacts of CAVs.

1.2. Organization of the Report

The remainder of the report is organized into seven sections. Section 2 summarizes a brief literature review of existing studies and practices on identifying the effect of different levels of CAVs on operations, safety, and the economy. The study methodology is explained in Section 3. Section 4 details the methodology adopted to calibrate and validate the simulation model. The approach adopted for modeling CAVs, and the scenarios generated to investigate the impact of CAVs on operations, safety, and the economy are also explained in Section 4. The results related to the impact of varying levels of CAVs and their varying penetration on operations, safety, and the economy are summarized in Section 5. The findings from this study and concluding remarks are summarized in Section 6. Section 7 and Section 8 summarize the recommendations and the implementation and technology transfer plan.

2. Literature Review

Studies on CAVs have gained considerable attention in recent decades due to their anticipated benefits to traffic operations and safety. According to the Federal Highway Administration (FHWA), CAVs can improve the operational performance of traffic flow through reduced congestion, expanded vehicular capacity, and fuel efficiency (FHWA, 2022). Moreover, CAVs promise enhanced safety by reducing the number of crashes caused by human errors. In terms of the economy, CAVs have the potential to reduce travel costs, increase productivity, and create new job opportunities. However, as CAVs are expected to penetrate into the existing transportation system in six levels of automation (SAE, 2019), it is necessary to identify the effect of the mix of varying levels of CAVs on operations, safety, and the economy. This section includes a brief overview of the studies conducted to quantify the benefits of CAVs. A detailed synthesis of studies identifying the effect of CAVs on operations, safety, and the economy was shared with the North Carolina Department of Transportation (NCDOT) TCE 2020-01 Project 3 Steering and Implementation Committee as a separate document.

2.1. Effect of CAVs on Operations

The impact of CAVs on the operational performance of arterial streets is currently limited based on the existing research. Khan et al. (2017) conducted a study to assess the effectiveness of CAV-supported access control on arterial streets. Their findings revealed that converting driveway access from fully open to right-in-right-out, based on prevailing traffic conditions, can enhance traffic operations. Tafidis et al. (2019) examined the effects of autonomous vehicles (AVs) on intersection operations and performance. Their study demonstrated a significant improvement in intersection performance with the deployment of AV technology. Simulation results indicated a 50% reduction in total vehicle delay at a controlled cross-intersection, with 100% market penetration of AVs.

Mathew et al. (2020) investigated the impact of different CAV penetration rates on travel time, delays, and the number of stops within an arterial street in Charlotte, NC. They revealed substantial improvements in travel time on the studied corridor as market penetration of CAVs increased. Additionally, they observed a 40% reduction in the total number of stops within the corridor when CAV market penetration reached 100%.

Fagnant and Kockelman (2015) highlighted that CAVs could increase mobility for young and elderly individuals, change parking patterns, increase road capacity, and increase car- and ride-sharing possibilities. Auld et al. (2017) employed advanced traffic simulation techniques and observed that CAVs could increase vehicle miles traveled (VMT) due to reduced travel times and migration effects from other modes. The advanced auto platooning capabilities and coordinated adaptive cruise control (CACC) in CAVs were found to improve road capacity (Arbib & Seba, 2017). Furthermore, Ye and Yamamoto (2018) demonstrated through microscopic simulation techniques that the capacity of road networks can increase with the penetration rate of CAVs.

In summary, a fully developed CAV environment unquestionably enhances road operational performance. However, the transition from nearly 0% to 100% CAV penetration poses significant challenges. Increasing the market penetration of CAVs is expected to introduce complexity into the current transportation system. This complexity arises from vehicles with varying levels of connectivity and automation and their interaction with each other and HDVs.

2.2. Effect of CAVs on Safety

In the case of studies quantifying the effect of CAVs on safety, researchers globally have adopted a microsimulation approach to evaluate the effect of CAVs on traffic safety at varying penetration levels considering the unavailability of crash data. The CAVs were simulated by developing a sequence of control logic and motion planning algorithms. A few studies modeled CAVs by modifying the parameters of the car-following and lane-change models. Conflict frequency, conflict rate (ratio of the number of potential conflicts/collisions to throughput), and crash rate were indicators to quantify the effect of CAVs on traffic safety.

Derbel et al. (2012) investigated the impact of mixed traffic comprising vehicles equipped with adaptive cruise control (ACC) in a crash scenario. The study noted enhanced safety and reduced crash risk when vehicles with ACC were involved. Rahman et al. (2019) investigated the impacts of connected vehicles (CVs) with and without platooning. They reported a significant enhancement in safety with a minimum penetration rate of 30%. They also concluded that CVs with platooning outperformed the effects of the absence of platooning, especially with penetration rates of 50% or higher. Wu et al. (2020) evaluated the impact of integrating CVs with variable speed limits (VSL) on freeway traffic safety in foggy conditions using VISSIM. They revealed that the integration of VSL and CVs was observed to perform better in terms of both safety and operations (Wu et al., 2020). Adomah (2020) analyzed the impacts of connected trucks on the I-80 corridor in Wyoming. The corridor's share of human-driven trucks (30%) was replaced with connected trucks. The study reported that the number of truck conflicts reduced with increased penetration of connected trucks. Zuo et al. (2020) observed that using the reinforcement learning algorithm for CAVs led to reduced pedestrian-vehicle conflicts and lower travel times at signalized intersections.

Jeong et al. (2014) investigated the impact of inter-vehicle safety warning information systems (ISWS) on traffic safety. The driver behavior captured using probe vehicles was inputted into the VISSIM simulation, and the surrogate safety assessment model (SSAM) was used to assess the number of conflicts. Rear-end conflicts were observed to reduce with an increase in the penetration rate. Li et al. (2016) evaluated the impact of integrating infrastructure to vehicle (I2V) with ACC and VSL in different combinations on traffic safety. Time-exposed time-to-collision (TET) and time-integrated time-to-collision (TIT) were considered as surrogate safety measures. They concluded that integrating technologies established better results compared to individual effects. Employing a similar methodology, Li et al. (2017a) evaluated the effects of ACC on the safety of freeways. Enhanced safety was observed with the increase in penetration rates. However, a combination of ACC and VSL was observed to produce the best results. Li et al. (2017b) also investigated the impacts of CACC on freeway rear-end crash risk.

The study noted a significant reduction in crash risk with CACC, while the TET and TIT were reduced by over 90%.

Yue (2020) probed into integrating CVs with different driver assistance systems to investigate the effects of integrating CV technology with other systems. A nearly 70% reduction in crashes could be achieved with the integration. The forward collision warning (FCW) system could reduce the rear-end crash risk by 35% in foggy conditions. Morando et al. (2018) concluded that CAVs significantly improved safety. On the other hand, Sinha et al. (2020) concluded that the safety benefits of CAVs are not related to the market penetration rate and can only be achieved at 100% CAVs penetration. Rahman and Abdel-Aty (2018) reported that CV technology significantly improves longitudinal safety compared to non-CVs at road segments and intersections on arterials. Virdi et al. (2019) reported that under lower penetration of CAVs, conflicts would increase at signalized intersections. Using a microsimulation approach, Oikonomou et al. (2023) revealed that crash rates would be significantly lower under the higher market penetration rate of CAVs. Similar compelling benefits of CAVs were also reported by Papadoulis et al. (2019) and Mourtakos et al. (2021). Garg and Bouroche (2023) reported that CAVs could significantly improve mixed traffic safety in the presence of unreliable V2V communication. They reported that conflicts were reduced by 66.7% at a 70% penetration rate of CAVs. Fagnant et al. (2015) estimated that introducing CAVs would result in safer travel. Beiker et al. (2012) discussed the challenges in classifying crash situations in CAVs and their implications for insurance companies.

2.3. Economic impacts of CAVs

Researchers in the past also attempted to quantify the economic impacts of CAVs. Clements and Kockelman (2017) estimated the potential economic impacts of CAVs, including reduced costs for truck drivers, lower insurance claims, and savings for individuals. Some researchers also focused on the effect of variations in the energy efficiency of CAVs on energy use at a particular travel demand (Greenblatt and Saxena, 2015; Lokhandwala and Cai, 2018).

Soteropolous et al. (2019) reviewed modeling studies. Their study indicated that CAVs may increase VMT and lead to reductions in the use of public transport. Kröger et al. (2018) developed a travel demand model. They found that integrating CAVs could increase VMT and decrease non-motorized and public transport mode share.

2.4. Research Gaps and Research Questions

Overall, studies on CAV operations have shown potential benefits regarding congestion reduction and travel time savings. Safety-related studies have highlighted the potential for safer travel, but concerns have been raised regarding liability and public acceptance. Economic studies have presented varying scenarios, including potential cost savings for individuals and reductions in energy consumption, but also the possibility of increased VMT and decreased use of public transport.

Although studies in the past quantified the economic impacts of CAVs considering induced traffic demand and anticipated benefits of CAVs, considering the safety and liability concerns, their adoption by private users and as a shared mode of transportation are unidentified. Therefore, it is necessary to quantify the economic impacts of CAVs in terms of matrices that could be used to quantify the operational, safety, and economic benefits of CAVs corresponding to their penetration.

Most studies focused on considering a particular level of automation to quantify the operational and safety benefits compared to HDVs. However, varying levels of CAVs and HDVs will coexist for a considerable time. A mixed traffic environment (heterogeneity due to varying levels of CAVs and HDVs) would have significant operational and safety implications because of uncertainty in vehicle-vehicle interactions (interaction between HDVs and CAVs and interaction between varying levels of CAVs). Therefore, for a comprehensive understanding of the effect of CAVs, it is necessary to identify the benefits of CAVs corresponding to different traffic mix conditions. This study provides answers to the following questions.

- How does the penetration of different levels of CAVs and HDVs influence the operational performance of traffic flow?
- How does the penetration of different levels of CAVs and HDVs influence the number of crashes?
- Do the operational and safety benefits of CAVs vary with road functional class?
- How does the penetration of different levels of CAVs influence the economy for different road functional classes?

This research quantifies the effects of varying levels of CAVs on operations, safety, and the economy under varying penetration and traffic volume scenarios for freeways and arterial streets. The findings from this study would help quantify the effect of a mix of different levels of CAVs on various aspects of the transportation system and enable practitioners and policymakers to develop policies and regulations to accommodate these impacts.

3. Study Methodology

This section provides an overview of the methodological framework adopted in this study. The methodological framework used in this study is shown in Figure 1. The framework consists of five major steps. They are:

- Identifying best practices and approaches to investigate the effect of CAVs
- Simulation modeling and scenario generation
- Effect of CAVs on the operational performance of traffic flow
- Effect of CAVs on traffic safety
- Economic impact of CAVs

A brief explanation of each step shown is explained next.

3.1. Identifying Approach to Investigate the Effect of CAVs

The authors conducted a comprehensive literature review to identify the best practices and methods used in existing literature for quantifying the effect of CAVs on operations, safety, and the economy. The microsimulation approach is the most suitable technique considering the unavailability of real-world CAVs data. The "data" is a broad term; however, the word "data" essentially covers a spectrum of data related to travel times, traffic volumes, and crashes.

Amongst various microsimulation tools, PTV Vissim is widely used in the literature because of its flexibility in modeling CAVs. Therefore, the authors used PTV Vissim in this study. Further, to mimic the behavior of different levels of CAVs, this study identifies driving behavior parameters for each level of CAV and the forecasted penetration of various levels of CAVs.

3.2. Simulation Modeling and Scenario Generation

The study designers selected two networks, one in Charlotte, NC, and the other in Raleigh, NC, for the study. The networks in this study have varying road functional classes (freeways, speed limits, and intersection types).

The first microsimulation model is for the network with the freeway corridor on I-85 and an arterial street corridor on Mallard Creek Church Rd in the Charlotte area, and the second microsimulation model is for the network with a freeway corridor in the Raleigh area. The study incorporates details such as road geometry, desired speed distributions, traffic volume composition and turning proportions, vehicle routes, signal plans, and phasing into the network using real-world data collected from multiple sources.

The authors conducted a sensitivity analysis to identify the sensitive Weidemann 99 driving behavior parameters. Then they adopted an iterative method to calibrate the driving behavior parameters for the base traffic condition. The driving behavior parameters were calibrated by minimizing the error between the observed and simulated travel times. The study authors modified the driving behavior parameters to model varying levels of CAVs. Level 1, Level 2, and Level 3 CAVs were modeled using the driving behavior parameters reported in the literature.

On the other hand, the study used the driving behavior parameters defined in the CoExist model to model Level 4 and Level 5 CAVs. The forecasted penetration rates for varying levels of CAVs were defined based on the literature.

The study authors generated a total of thirteen scenarios with varying penetration of different levels of CAVs. They tested the scenarios for three traffic volumes, including existing peak hour traffic volumes, off-peak traffic volumes (half of the peak hour demand), and forecasted peak traffic volumes for 2030.

3.3. Effect Of CAVs on Operational Performance of Traffic Flow

The study used variations in travel time, the percentage reduction in travel time and delay, and variation in buffer time to quantify the effect of CAVs on the operational performance of traffic flow. The travel time data were extracted from the simulation model at every five-minute interval for each traffic volume level and scenario. The authors developed box plots from travel time data to visualize the variation in travel time across each scenario. They developed additional box plots by traffic volume level and road functional classes. Further, considering the base scenario (100% HDVs) as a reference, the authors estimated a percentage reduction in travel time and delay for all the scenarios. Finally, they estimated the buffer time for each scenario and compared it to the base scenario to quantify the impact of CAVs on travel time reliability. The results and discussion section provides a detailed description of the methodology.

3.4. Effect of CAVs on Traffic Safety

The authors extracted vehicle trajectories for each simulation run and scenario from the microsimulation model. The trajectories were further processed using SSAM. The processed data from SSAM contained information on the type of conflict and its corresponding time-to-collision (TTC) value. The TTC value reflects the temporal nearness between two vehicles. A smaller TTC value indicates nearness between two vehicles and, therefore, a higher probability of a crash and vice-versa. The authors used the angle between the vehicles to identify different conflict types. An angle of 30° characterizes rear-end and lane-change conflicts, whereas 85 ° characterizes lane-change and crossing conflicts. The study employed an EVT-based POT approach to estimate the number of crashes from conflict data. Crashes are estimated by conflict type for each scenario and are compared with those in the base scenario to quantify the impact of CAVs on traffic safety.

3.5. Economic Impacts of CAVs

The literature reviewed showed numerous benefits of CAVs regarding travel time and crashes. In addition, studies also revealed an induced effect of CAVs due to increasing ridership with zero occupant trips. CAVs can serve as a potential mode of travel for captive rides relying on public transportation. In contrast, some studies indicated that CAVs would be a potential ridesharing option using shared autonomous taxis. Although many studies are available on quantifying the economic impact of CAVs, all the studies are conducted with underlying assumptions of CAVs' adoption by private users and their use as shared modes of transport. However, considering the recent crash involvement of vehicles with Level 3 automation, there is uncertainty about using CAVs for zero-occupant trips.

Considering the vast uncertainties with the future adoption of CAVs, the scope of economic analysis in this study is limited to quantifying the economic impact of CAVs considering the reduction in travel times and crashes for existing traffic conditions (without considering induced demand, i.e., the effect of induced demand assumed to be covered within the demand level). The study used the buffer time and the number of crashes estimated for each scenario to quantify the economic impact of CAVs. The net present value of buffer time was estimated from buffer time results. The study adopted the generalized value of buffer time per minute for North Carolina, as reported by Pulugurtha et al. (2017, 2019, 2021). Interested readers are encouraged to refer to Pulugurtha et al. (2017) and Duddu et al. (2018) to apply the generalized value of buffer time for analyzing transportation projects and alternatives.

The study estimated buffer time cost per vehicle per mile for each scenario for freeway and arterial streets. Further, the net present value of crash cost per mile for the selected corridors and scenario was estimated using the standardized crash cost estimates for North Carolina (NCDOT, 2019). The authors compared the buffer time cost and crash cost for each scenario to that of the base scenario to quantify the impact of CAVs on the economy.

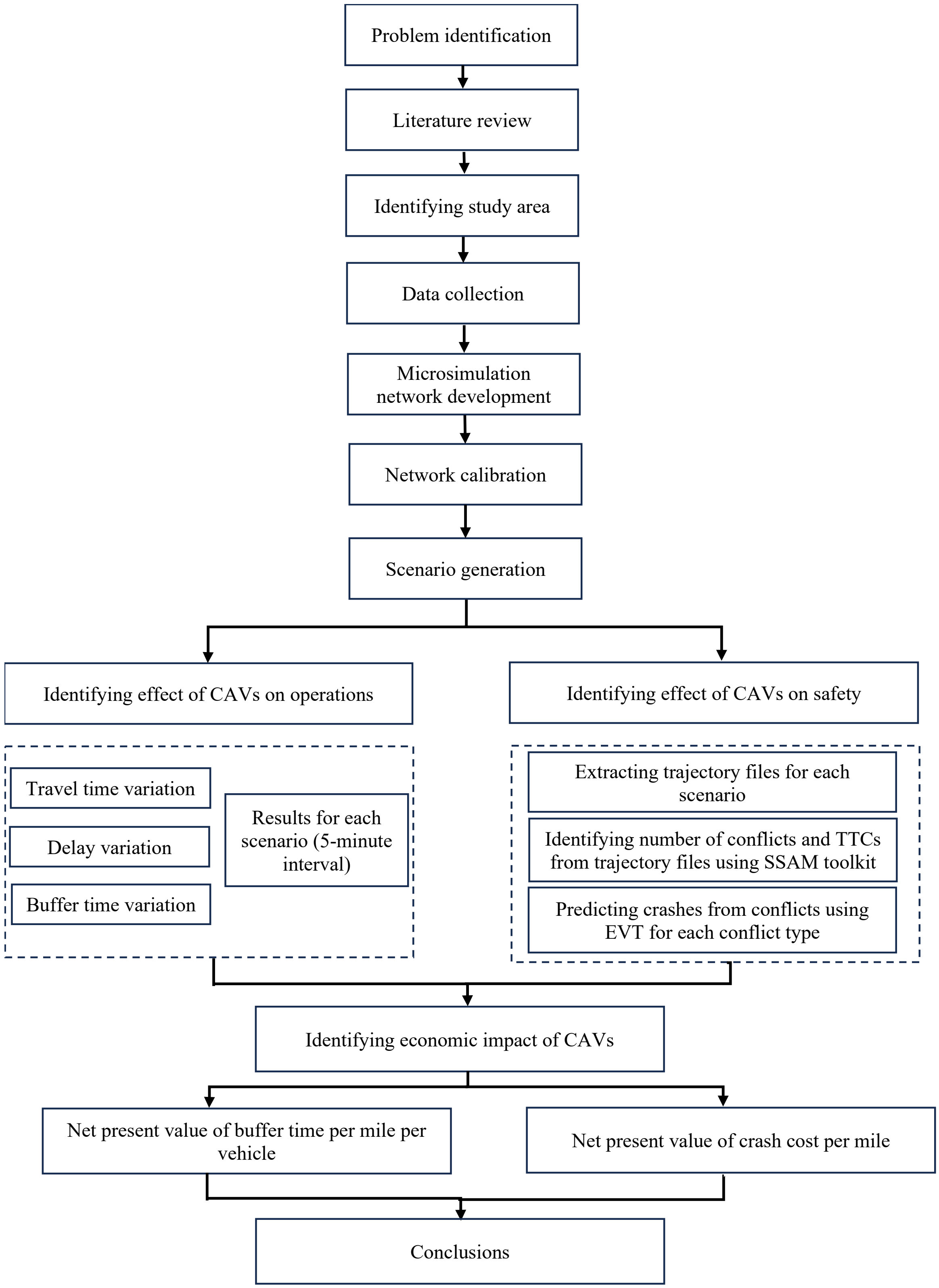


Figure 1. Methodological framework

4. Simulation Modeling: Calibration and Validation

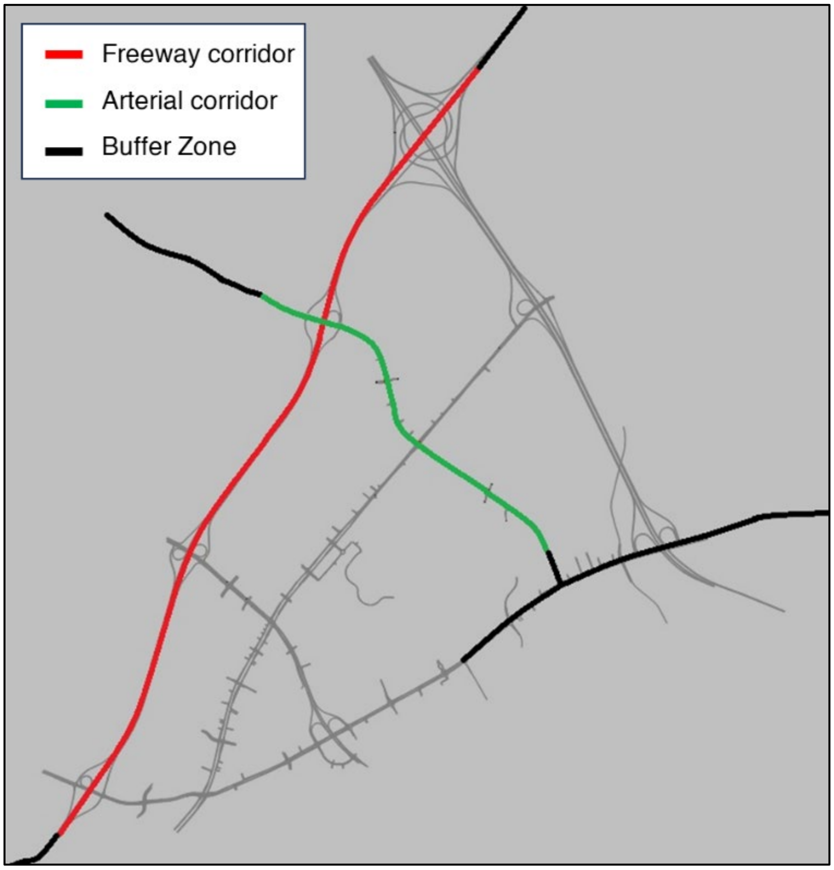
The reliability of the results from a microsimulation approach is governed by how well the simulation model represents the field (base scenario) conditions. Therefore, a robust calibration methodology is imperative for deriving unbiased conclusions regarding the effect of CAVs on operations, safety, and the economy. The methodology adopted for developing and calibrating the simulation model is explained next.

4.1. Model Development and Calibration

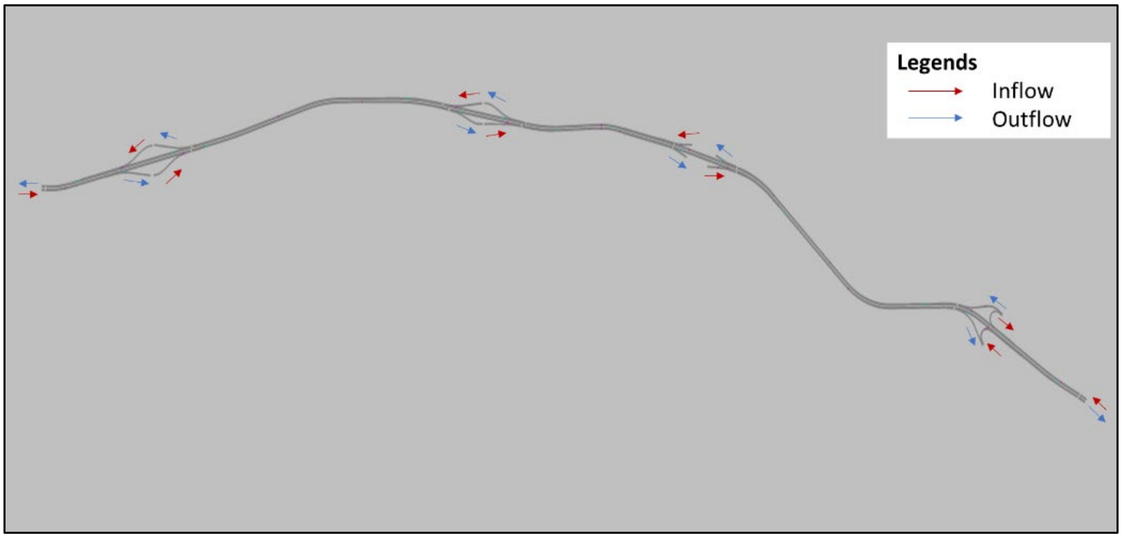
A VISSIM simulation model was developed to investigate the effect of varying levels of CAVs on traffic operations, safety, and the economy.

The study authors selected two networks, one in Charlotte, NC, and the other in Raleigh, NC. The first network is a 5.3-mile freeway on I-85 between Exit 43 (NC 49) and Exit 48 (I-485) and a 2-mile arterial street on E Mallard Creek Church Rd between the entry ramp to I-85 and the intersection with NC 49 in Charlotte. The second network is an 8.6-mile freeway in Raleigh. For the network in Charlotte, traffic volume and turning movement counts were obtained from the City of Charlotte Department of Transportation (CDOT) and the NCDOT. The speed/travel time data for off-peak and peak-hour were extracted from private data sources and used for calibration.

The authors built the selected networks in the microsimulation software. Characteristics such as existing roadway dimensions, gradient of roadway, number of lanes, speed limit, and turning lanes at intersections on connecting arterial streets were created using street-view in Google Earth tool and Google Maps. Figure 2 shows the study corridors in Charlotte and Raleigh. For the network in Charlotte, the study included other arterial streets connecting to the freeways and arterial streets in the network. A two-mile buffer was used at each end of the corridors to achieve stable flow in the simulation. Further, the authors incorporated an initialization or warm-up period of 30 minutes before extracting outputs. This ensured the system reached equilibrium (Dumitru and Pulugurtha, 2021; Preston and Pulugurtha, 2021; Gore et al., 2022).



(a) Charlotte Network



(b) Raleigh Network

Figure 2. Study networks

The authors inputted the stochastic variables, such as traffic volume count, routing decisions, and turning proportions into the simulation model. They employed a traffic volume balancing technique developed by the Wisconsin DOT (WisDOT, 2019) to balance the entry and exit volumes.

VISSIM includes the distribution of vehicle acceleration and deceleration performances as a function of speed profile. The authors assigned specific speed distributions to cars and trucks using the travel time data extracted from the private data source.

The developed simulation model was calibrated by optimizing the Weidemann 99 driving behavior parameters. The model calibration methodology is presented in Figure 3.

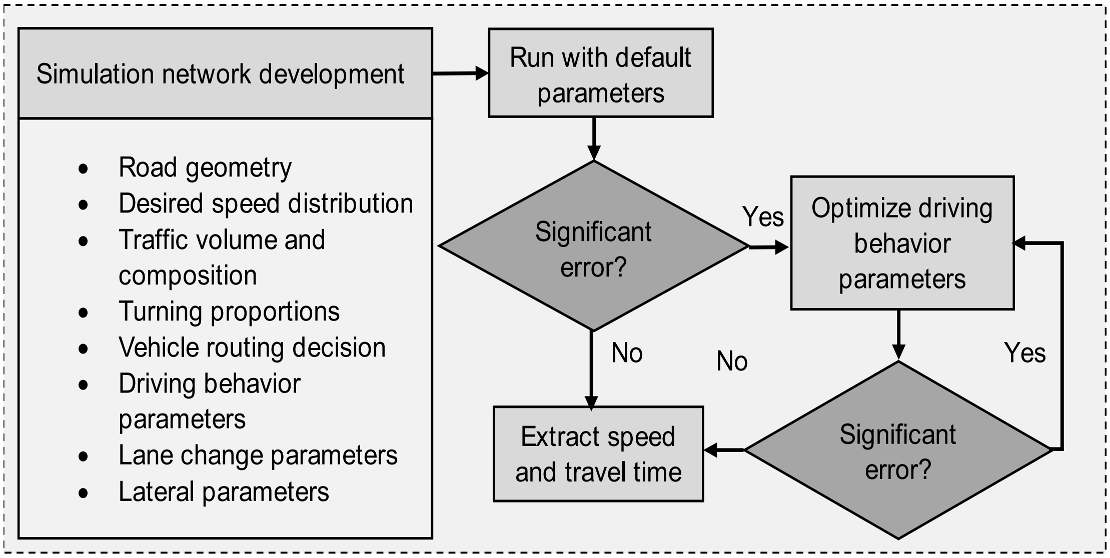


Figure 3. Simulation calibration methodology

The sensitive driving behavior parameters influencing the simulation results were identified using a trial and error method. Travel time was considered the measure of effectiveness (MOE). The driving behavior parameters were varied between the lower and upper limits defined by the Wisconsin DOT (WisDOT, 2021). Based on the trial and error method, CC0, CC2, CC4, CC5, CC7, CC9, and the safety reduction factor were identified as the most sensitive parameters. The study authors calibrated the resulting driving behavior parameters (sensitive parameters) by minimizing the error between the observed and simulated travel times. The study adopted an iterative procedure to calibrate the driving behavior parameters. The mean absolute percentage error (MAPE) was used to measure the performance. The driving behavior parameters corresponding to the minimum MAPE values were considered optimized driving behavior parameters. The optimized driving behavior parameters for the network in Charlotte and Raleigh and the default parameters used to initialize the calibration procedure are shown in Table 1.

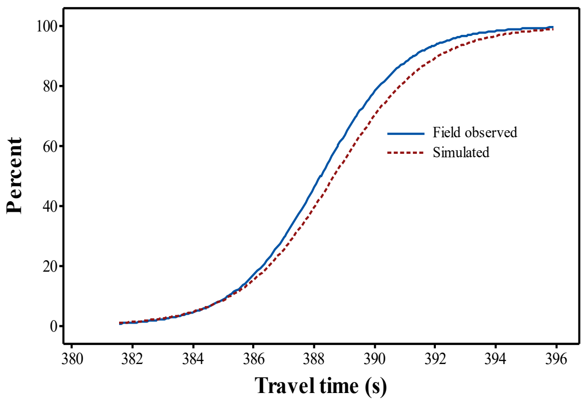
Table 1. Calibrated driving behavior parameters

Car-Following	Default	Calibrated	
		Charlotte	Raleigh
CC0 (ft)	4.92	5.65	4.92
CC1 (s)	0.90	0.90	0.9
CC2 (ft)	13.12	13.77	13.12
CC3 (s)	-8.00	-8.00	-8.00
CC4 (ft/s)	-1.14	-1.25	-0.35
CC5 (ft/s)	-1.14	1.25	0.35
CC6 (10^{-4} rad/s)	11.44	11.44	11.44
CC7 (ft/s^2)	1.15	1.15	0.82
CC8 (ft/s^2)	11.48	11.48	11.48
CC9 (ft/s^2)	4.59	4.59	4.92
Lane-Change	**Default**	**Calibrated**	
		Charlotte	**Raleigh**
Maximum deceleration own (ft/s^2)	-13.12	-13.12	-13.12
Maximum deceleration trailing (ft/s^2)	-13.12	-13.12	-13.12
-1ft/s^2 per distance own (ft)	100	200	100
-1ft/s^2 per distance trailing (ft)	100	200	100
Accepted deceleration own (ft/s^2)	-3.28	-3.28	-3.28
Accepted deceleration trailing (ft/s^2)	-3.28	-3.28	-3.28
Waiting time before diffusion (s)	60	60	60
Min. clearance front/rear (ft)	1.64	1.64	1.64
Safety distance reduction factor	0.6	0.75	0.75
Maximum deceleration for cooperative breaking (ft/s^2)	-9.84	-9.84	-9.84

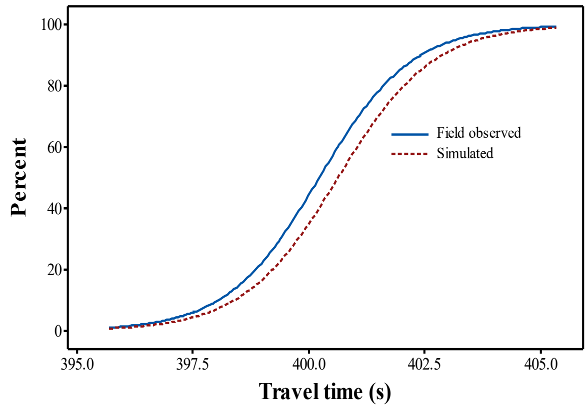
4.2. Model Validation

Figure 4 illustrates the cumulative distribution plot of the field observed and simulated travel times for the selected freeway corridor in Charlotte. Figure 4 shows that the travel time obtained through the simulation model is close to those observed in the field. Consistent trends were observed for northbound and southbound directions. MAPE values were computed and are estimated as 3.69% and 5.89% for northbound and southbound directions, highlighting robust calibration of the simulation model (driving behavior parameter). Further, a two-sample Kolmogorv-Sminirov (K-S) test was performed at a 0.05 significance level. It was concluded that the K-S statistic was lower than the critical value at a 0.05 significance level for both northbound and southbound directions. This implies that the simulation model is well-calibrated in terms of travel times. The study authors conducted a similar exercise for the selected arterial street in Charlotte and the selected freeway corridor in Raleigh. The MAPE for the selected arterial street in Charlotte varied from 9.26% in the eastbound direction to 12.09% in the westbound direction, whereas a MAPE value of less than 15% was observed for the selected freeway corridor in

Raleigh. Therefore, the developed simulation models are calibrated and can represent the existing field conditions.



(a)



(b)

Figure 4. Cumulative travel time distribution profiles for (a) northbound and (b) southbound directions of the selected freeway corridor in Charlotte

4.3. CAV Modeling

Per the current practice, one of the two methodologies could be adopted to model CAVs in VISSIM: (a) internal modeling methodology and (b) external modeling methodology. In the internal modeling methodology, the behavior of CAVs in terms of car-following and lane-change is defined to capture CAVs and their interaction with HDVs. On the other hand, in external modeling, a sequence of control logic and motion planning algorithms for CAVs are developed to replace the default driving behavior models (Cisco, 2017). This study adopted an internal modeling methodology.

The behavior of CAVs is mainly influenced by three attributes: gaps between leading and following vehicles, cooperative behavior of vehicles, and parameters related to vehicular interaction (Yang et al., 2020). Driving behavior parameters were adjusted to simulate the behavior of CAVs. In addition, advanced merging and cooperative lane change behavior were considered exclusively for Level 3, Level 4, and Level 5 CAVs. Based on test vehicle studies and empirical results, this study used driving behavior parameters recommended in those studies to mimic Level 1, Level 2, and Level 3 CAVs (Sukennik, 2020; Goodall et al., 2020). Moreover, to simulate Level 4 and Level 5 CAVs, the automated vehicle-related parameters for all-knowing behavior in VISSIM based on the CoExist Project were used (Sukennik, 2020, Morando et al., 2018).

Table 2 shows the parameters used for modeling different levels of CAVs. In addition to the driving behavior parameter for individual vehicle types (such as HDVs and varying levels of CAVs), the following behavior of vehicles by the type of leading vehicle was also defined. The idea behind this is that the headway maintained by the following vehicle depends on the type of the leading vehicle. CC0 and CC1 parameters were defined separately for the leading and following vehicle types to incorporate this behavior.

Table 2. Driving behavior parameters to mimic behavior of different levels of CAVs

Parameters	Level 1	Level 2	Level 3	Level 4	Level 5
CC0 (ft)	4.92	4.92	3.28	3.28	3.28
CC1 (s)	0.60	0.60	0.60	0.60	0.60
CC2 (ft)	6.56	6.56	0.00	0.00	0.00
CC3 (s)	-8.00	-8.00	-6.00	-6.00	-6.00
CC4 (ft/s)	-1.15	-1.15	-1.15	-1.15	-1.15
CC5 (ft/s)	1.15	1.15	1.15	1.15	1.15
CC6 (10^{-4} rad/s)	0.00	0.00	0.00	0.00	0.00
CC7 (ft/s^2)	0.82	0.82	0.33	0.33	0.33
CC8 (ft/s^2)	13.12	13.12	13.12	13.12	13.12
CC9 (ft/s^2)	6.56	6.56	6.56	6.56	6.56
Safety distance reduction factor	0.60	0.60	0.50	0.50	0.50
Lateral position	Any	Middle	Middle	Middle	Middle
Connectivity	No	No	No	Yes	Yes

Level 4 and Level 5 CAVs communicate with other vehicles in the traffic stream and accordingly plan their trajectory. A simulation package cannot directly achieve vehicle connectivity (e.g., vehicular ad-hoc network). An indirect simulation of CAVs subsystems (sensing, perception, planning, and control) and behavior with reasonable assumptions was developed. The sensing subsystem was indirectly represented by the ability to collect nearby vehicles' data up to 840 ft (256 m). The perception and planning subsystem using the other vehicles' information, plans the motion or trajectory of the vehicle based on the car-following and lane change parameters inputted for the Level 4 and Level 5 CAVs. The vehicle connectivity approach used in this study is similar to that of Papadoulis et al. (2019).

4.4. Scenario Generation

As the penetration of CAVs will vary with time, it is necessary to identify the forecasted penetration of CAVs to mimic the exact behavior of traffic over time. Table 3 summarizes the penetration of varying levels of CAVs for different scenarios of the Charlotte network.

For Sc1, the penetration of Level 1 and Level 2 CAVs was decided based on the share of these vehicle types in the crash database. Gajera et al. (2022) and Gajera et al. (2023) analyzed the Fatality Analysis and Reporting System (FARS) database. From 2016 to 2019, these studies revealed that Level 1 and Level 2 CAVs had a share of ~10% and ~5% in the crash database. Therefore, the same penetration levels were used for Sc1. In the case of Sc-2, the FARS 2020 data was analyzed. It was observed that the share of Level 1 CAVs was constant compared to the 2016-2019 database, the share of Level 2 CAVs increased from ~5% to ~7.5%, and Level 3 CAVs were observed to have a share of ~2.5%. Therefore, the same penetration levels were used for Sc2. The penetration levels for Sc3 to Sc6 were decided by

assuming that penetration of Level 2 and Level 3 CAVs would start to increase and Level 4 CAVs will slowly penetrate the market. Sc7 to Sc12 represent scenarios with only CAVs.
The scenarios with different penetration levels were simulated for three varying levels of traffic volumes: (a) off-peak hour traffic volumes (low), (b) peak hour demand (normal), and (c) forecasted peak hour traffic volumes for 2030 (high). This study used a growth factor of 3% to estimate peak hour demand for 2030. For each simulation, five runs at varying random seeds were performed. Therefore, 195 simulations (13 scenarios * 3 demand levels * 5 simulation runs) for each corridor were carried out.

Table 3. Penetration of varying levels of CAVs for different scenarios (Charlotte)

Scenario	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5	Heavy Vehicles
Base	98	0	0	0	0	0	2
Sc1	83	10	5	0	0	0	2
Sc2	78	10	7.5	2.5	0	0	2
Sc3	68	10	15	5	0	0	2
Sc4	48	10	25	10	5	0	2
Sc5	28	10	30	20	10	0	2
Sc6	5	10	38	25	15	5	2
Sc7	0	5	33	30	20	10	2
Sc8	0	0	15	38	30	15	2
Sc9	0	0	5	30	25	38	2
Sc10	0	0	0	5	35	58	2
Sc11	0	0	0	0	25	73	2
Sc12	0	0	0	0	0	98	2

Since the proportion of heavy vehicles was higher for the Raleigh corridor, the penetration rates for each scenario are different, as shown in Table 4.

Table 4. Penetration of varying levels of CAVs for different scenarios (Raleigh)

Scenario	Level 0	Level 1	Level 2	Level 3	Level 4	Level 5	Heavy Vehicles
Base	94.5	0	0	0	0	0	5.5
Sc1	79.5	10	5	0	0	0	5.5
Sc2	74.5	10	7.5	2.5	0	0	5.5
Sc3	64.5	10	15	5	0	0	5.5
Sc4	44.5	10	25	10	5	0	5.5
Sc5	24.5	10	30	20	10	0	5.5
Sc6	5	10	34.5	25	15	5	5.5
Sc7	0	5	29.5	30	20	10	5.5
Sc8	0	0	15	34.5	30	15	5.5
Sc9	0	0	5	30	25	34.5	5.5
Sc10	0	0	0	5	35	54.5	5.5
Sc11	0	0	0	0	25	69.5	5.5

Sc12	0	0	0	0	0	94.5	5.5

5. Results & Discussion

This section summarizes and discusses the results obtained for the network in Charlotte. The results are explained by the road functional class, i.e., freeway corridor and arterial street. The results of the network in Raleigh are summarized in Appendix A.

It is essential to mention that the entire roadway network was discretized into links with varying lengths based on specific criteria, such as interchanges for freeways and intersections for arterial streets. This study analyzed seven freeway links and eleven arterial street links in each direction. The other 19 links were considered for developing the simulation model. The simulation model results are extracted for each link and then aggregated for the entire corridor (i.e., freeway and arterial streets) to ensure consistency in presenting the results. The following subsections present the results related to the effect of CAVs on operations, safety, and economy.

5.1. Effect of CAVs on the Freeway and Arterial Street Operations

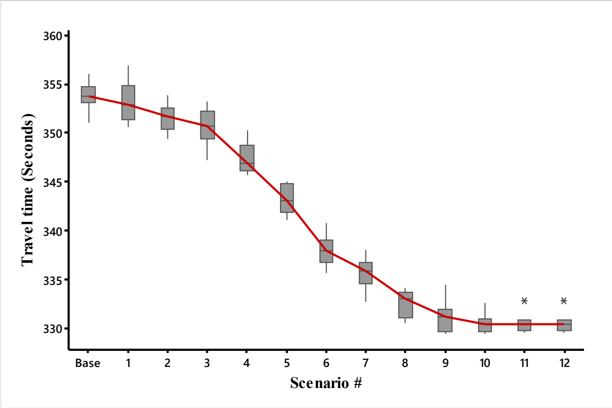
CAVs are expected to create a more stable flow by stabilizing car-following and lane-changing behavior. Therefore, an effect on travel time, delay, and travel time reliability is apparent. Variations in travel times, the percentage reduction in travel time and delay, and buffer time are considered MOEs to quantify the effect of varying levels of CAVs and their penetration on the operational performance of freeways and arterial streets. The simulation results for each scenario were collected at 5-minute time intervals.

5.1.1. Effect of CAVs on Travel Time

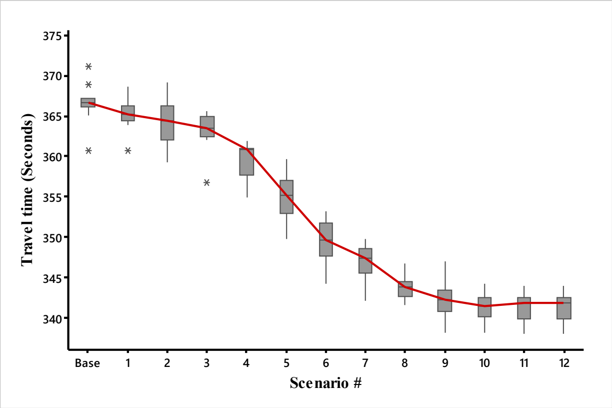
The variation in travel time for varying scenarios is visualized using box plots, as shown in figures 5 and 6. Separate box plots were prepared for each traffic volume level by direction of travel to comprehend the variation in operational performance by traffic volume level and penetration of varying levels of CAVs. The results are discussed for the Charlotte network, and the results for the Raleigh network are discussed in Appendix A.

5.1.1.1. Freeways

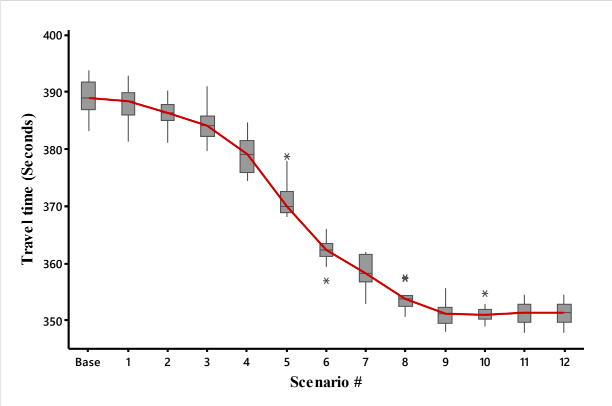
The variation in travel time for each scenario and traffic volume level for freeways is illustrated in Figure 5.



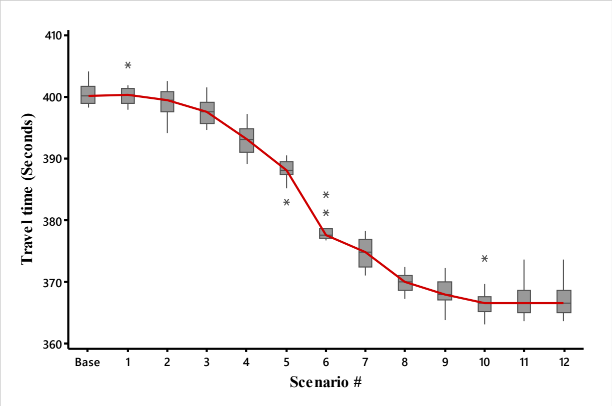
(a) Northbound low traffic



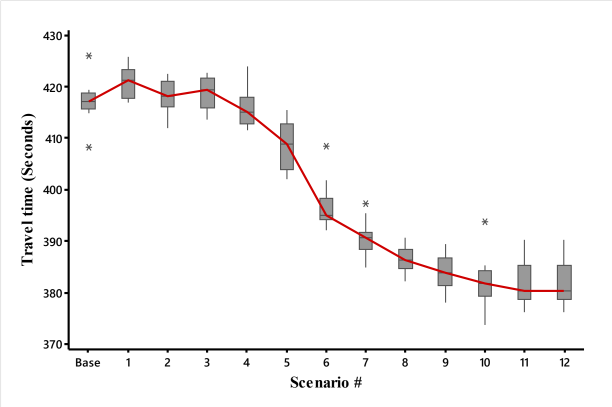
(b) Southbound low traffic



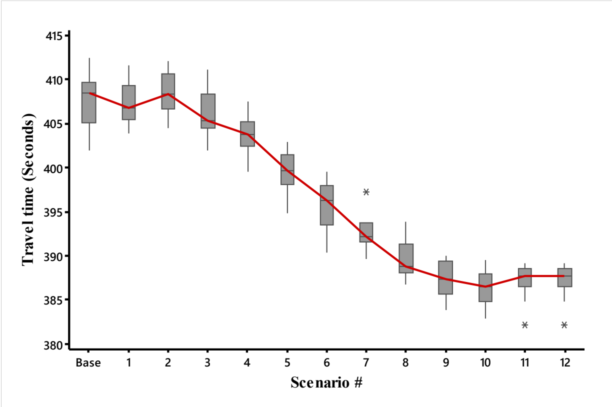
(c) Northbound normal traffic



(d) Southbound normal traffic



(e) Northbound high traffic



(f) Southbound high traffic

Figure 5. Variation in travel time for the selected freeway corridor in Charlotte

Figure 5 indicates that the mean travel time for freeways decreases from Sc1 to Sc12 compared to the base scenario. This implies that an increase in the penetration of CAVs would reduce travel times. It is essential to understand that the reduction in travel time depends not only on the penetration of CAVs but also on the level of CAVs and the share of HDVs. For instance, until Sc4, there is a negligible reduction in travel time for all traffic scenarios. If the composition until Sc4 is inspected, it can be noted that HDVs dominate the traffic with a share of 48%, followed by Level 2 CAVs. The results until Sc4 indicate that higher penetration of Level 1 and Level 2 CAVs results in a marginal difference in travel times. However, from Sc5 to Sc8, there is a significant reduction in travel time, indicating that the increasing penetration of Level 3, Level 4, and Level 5 CAVs would significantly reduce the travel time. The share of HDVs is reducing gradually (less than 50%) from Sc5 to Sc8; therefore, the uncertainty in the interaction between HDVs and varying levels of CAVs reduces, significantly reducing travel times. Further, the variation in travel time is marginal from Sc8 to Sc12, indicating that penetration of Level 4 or Level 5 CAVs marginally reduces travel time compared to scenarios with higher penetrations of Level 3 CAVs.

In addition to the reduction in mean travel time, a significant reduction in the variance of the travel times can be observed. This study found consistent observations of varying traffic volume levels and direction of travel. Upon comparing the traffic volume levels, it can be inferred that travel time increases with an increase in traffic volume. This observation is consistent and supports the general theory that with an increase in traffic volume, vehicle-to-vehicle interactions increase, resulting in increased travel times.

The reduction in mean and variance of travel time for CAVs, even at similar traffic volume levels, can be attributed to (a) relatively lesser spacing between vehicles and (b) stable acceleration/deceleration, car-following, and lane-changing behavior. However, stabilizing the vehicle performance depends on the level of CAVs. Level 4 and Level 5, because of advanced communication capabilities, result in harmonized traffic flow conditions, thereby significantly reducing travel times even for similar traffic volume levels compared to other levels of CAVs.

A percentage (%) reduction in average travel time per vehicle for each scenario with respect to the base scenario was estimated to quantify the effect of CAV on travel time. The percentage reduction in travel time for “ScX” is estimated using Equation 1. The percentage reduction in travel time is computed for every 5-min.

$$\%\, reduction\ in\ TT\ (ScX) = \frac{(TT\ for\ base\ scenario - TT\ for\ ScX)}{TT\ for\ base\ scenario} * 100 \qquad (1)$$

where ScX represents the scenario. X takes a value of 1, 2, 3,…..12. TT is the travel time. A positive value indicates a reduction of travel time in ScX compared to the base scenario and vice versa.

The average percentage reduction in travel time for each scenario and traffic demand are summarized in Table 5.

Table 5. Average % reduction in travel time per vehicle for the selected freeway corridor in Charlotte

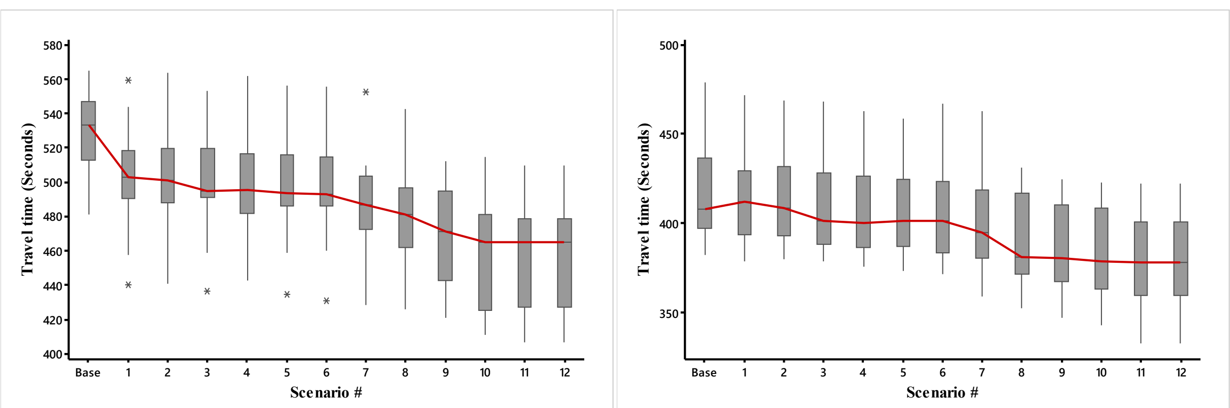
Scenario #	Northbound			Southbound		
	Low	Normal	High	Low	Normal	High
Sc1	0.18	0.30	-0.89	0.35	0.01	0.06
Sc2	0.63	0.66	-0.21	0.67	0.27	-0.21
Sc3	0.85	1.18	-0.43	0.88	0.73	0.36

Sc4	1.81	2.55	0.31	1.94	1.82	0.92
Sc5	2.98	4.53	2.01	3.12	3.12	1.95
Sc6	4.47	6.91	4.91	4.64	5.52	2.89
Sc7	5.10	7.83	6.39	5.39	6.42	3.66
Sc8	6.00	9.05	7.42	6.21	7.62	4.39
Sc9	6.40	9.72	8.03	6.65	8.09	4.94
Sc10	6.56	9.74	8.43	6.88	8.41	5.21
Sc11	6.54	9.72	8.47	6.90	8.33	4.98
Sc12	6.54	9.72	8.47	6.90	8.33	4.98

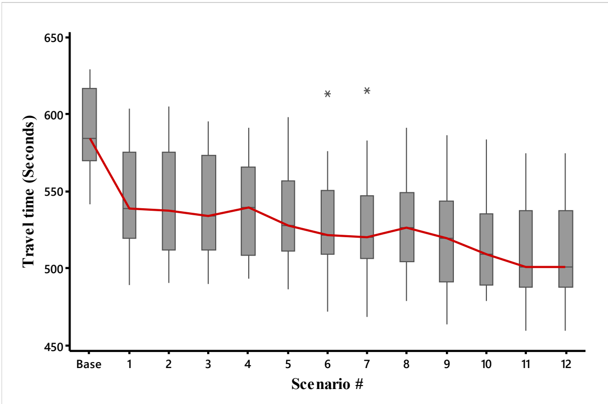
Table 5 shows the percentage reduction in travel time for the scenario compared to the base scenario. The results in Table 5 show that the percentage reduction in travel time increases with increasing penetration of CAVs on the selected freeway corridor. For low traffic volume, the maximum reduction in travel time is 6.54%. The reduction in travel time is highest for normal traffic scenarios, which is between 8.33% to 9.72%. The results for high-traffic volume scenarios significantly vary in both directions. The percentage reduction is 8.47% for the northbound direction. However, it is almost half (4.98%) for the southbound direction. In addition, it can be noted that the percentage reduction in travel time increases from Sc4 to Sc8, where HDVs are replaced by CAVs, and then stabilizes from Sc8 to Sc12. Consistent observations can be deduced for varying traffic volume levels and direction of travel.

5.1.1.2. Arterial Streets

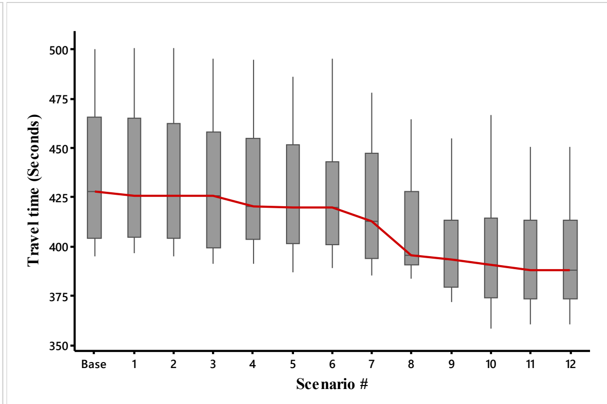
The variation in travel time for each scenario and traffic volume level for the selected arterial street is illustrated in Figure 6.



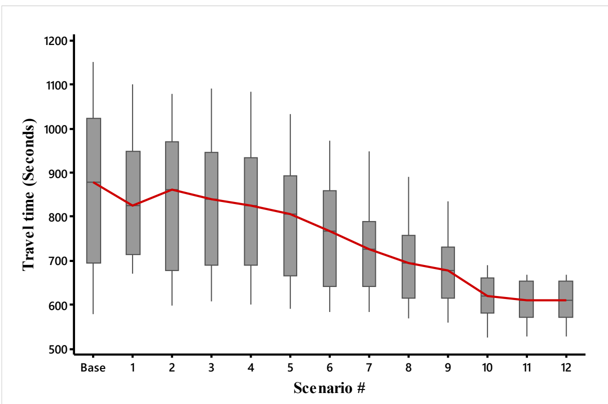
(a) Eastbound low traffic (b) Westbound low traffic



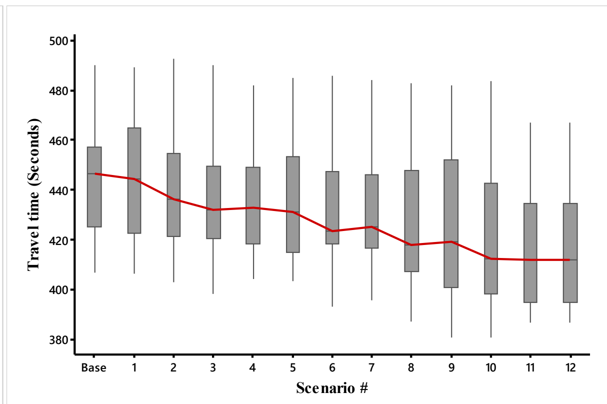
(c) Eastbound normal traffic



(d) Westbound normal traffic



(e) Eastbound high traffic



(f) Westbound high traffic

Figure 6. Variation in travel time for the selected arterial street in Charlotte

The travel time variation for the selected arterial street, when compared with the selected freeway corridor, reveals that the travel time variation due to CAVs also depends on the road functional class and traffic control characteristics. In the case of the selected arterial street, the trends in travel time variation from the base scenario until Sc4 are similar to the selected freeway corridor, indicating a marginal effect of CAVs on travel time, potentially due to uncertain vehicle-to-vehicle interactions caused by a mix of different levels of CAVs and HDVs. The trends in the case of the selected arterial street are not consistent for some scenarios. For instance, there is a significant reduction in travel time in Sc1 compared to the base scenario for the eastbound low and normal traffic volume conditions. However, the variation is negligible compared to other scenarios. The general trend shows a reduction in the mean and variance of travel time with increased penetration of CAVs.

The percentage reduction in travel time for each scenario is computed using Equation (1), and the results are summarized in Table 6.

Table 6. Percentage reduction in travel time per vehicle for the selected arterial street in Charlotte

Scenario #	Eastbound			Westbound		
	Low	Normal	High	Low	Normal	High
Sc1	4.85	7.95	2.37	0.11	0.14	0.21
Sc2	5.14	8.09	3.07	0.67	0.41	1.22
Sc3	5.52	8.49	3.80	1.31	1.23	1.63
Sc4	5.73	8.54	5.22	1.93	1.79	1.85
Sc5	6.05	9.22	8.42	2.03	2.22	2.23
Sc6	6.10	9.88	12.17	2.41	2.52	2.73
Sc7	7.67	9.80	15.44	3.58	3.48	3.14
Sc8	9.11	10.18	19.10	6.76	6.11	3.95
Sc9	11.29	11.87	21.35	7.44	8.11	4.66
Sc10	12.79	12.50	28.43	8.32	8.51	5.25
Sc11	13.10	13.48	29.60	8.83	9.25	6.15
Sc12	13.10	13.48	29.60	8.83	9.25	6.15

In the case of the selected arterial street, the percentage reduction in travel time values are positive for all scenarios, highlighting a reduction in travel time compared with the base scenario. Unlike the selected freeway corridor, the percentage reduction in travel time is higher (13.10% to 8.83%) for Sc12 in low-traffic conditions. Similarly, the percentage reduction in both directions is 13.48% and 9.25%, respectively, for normal traffic volume conditions. However, the reduction in travel time is significantly different for eastbound and westbound directions for high traffic volume. Unlike the selected freeway corridor results, the percentage reduction for the selected arterial street increases significantly from Sc8 to Sc12, where Level 1 and Level 2 CAVs are replaced with Level 3, Level 4, and Level 5 CAVS. This could be attributed to the communication of Level 3, Level 4, and Leve l5 CAVs with traffic signals.

Overall, it can be stated that CAVs significantly reduce travel time. The reduction in travel time is higher for arterial streets than freeways, attributed to the communication of CAVs with traffic signals on the arterial streets. The reduction in travel time for similar traffic volume levels increases with increased penetration of Level 4 and Level 5 CAVs.

5.2. Effect of CAVs on Delay

The effect of CAVs on travel time indicates a significant effect on delay. The delay can be computed as

$$Delay\ (s) = \ ATT - FFTT \qquad (2)$$

where ATT is the average travel time and FFTT is the free-flow travel time. The FFTT is the travel time corresponding to the speed limit. The ATT is computed for each scenario separately for every 5-min interval.

The variation in delay for different scenarios follows a similar trend to that of travel times and hence is not discussed.

The delay for each scenario is compared to the base scenario to quantify the effect of varying levels of CAVs on their penetration on delay. The percentage reduction in the delay is estimated using Equation 3.

$$\%\ reduction\ in\ delay\ (ScX) = \frac{(delay\ for\ base\ scenario - delay\ for\ ScX)}{delay\ for\ base\ scenario} * 100 \qquad (3)$$

where ScX represents the scenario. X takes a value of 1, 2, 3,…..12. A positive value indicates a reduction in delay for ScX compared to the base scenario and vice versa.

The average percentage reduction in average delay per vehicle for the selected freeway corridor and arterial street are summarized in Tables 7 and 8.

Table 7. Percentage reduction in delay per vehicle for the selected freeway corridor in Charlotte

Scenario #	Northbound			Southbound		
	Low	Normal	High	Low	Normal	High
Sc1	1.12	1.23	-3.14	2.05	0.01	0.19
Sc2	3.84	2.71	-0.79	3.93	1.12	-0.91
Sc3	5.18	4.90	-1.53	5.15	3.02	1.35
Sc4	11.10	10.65	1.03	11.39	7.60	3.57
Sc5	18.30	18.94	6.82	18.41	13.01	7.65
Sc6	27.41	28.94	16.78	27.37	23.02	11.36
Sc7	31.30	32.81	21.92	31.78	26.76	14.41
Sc8	36.85	37.90	25.48	36.61	31.79	17.32
Sc9	39.26	40.72	27.57	39.26	33.75	19.49
Sc10	40.25	40.76	28.91	40.58	35.09	20.52
Sc11	40.14	40.68	29.07	40.69	34.74	19.64
Sc12	40.14	40.68	29.07	40.69	34.74	19.64

Table 8. Percentage reduction in average delay per vehicle for the selected arterial street in Charlotte

Scenario #	Eastbound			Westbound		
	Low	Normal	High	Low	Normal	High
Sc1	8.76	13.25	3.27	0.21	0.25	0.38
Sc2	9.30	13.49	4.23	1.28	0.74	2.18
Sc3	9.98	14.17	5.23	2.48	2.24	2.93
Sc4	10.35	14.23	7.19	3.66	3.27	3.32
Sc5	10.93	15.38	11.58	3.86	4.04	3.99
Sc6	11.02	16.48	16.73	4.57	4.61	4.88
Sc7	13.87	16.34	21.24	6.79	6.35	5.62

Sc8	16.46	16.98	26.27	12.83	11.15	7.08
Sc9	20.42	19.80	29.36	14.12	14.81	8.35
Sc10	23.12	20.85	39.09	15.79	15.54	9.41
Sc11	23.68	22.48	40.71	16.76	16.89	11.02
Sc12	23.68	22.48	40.71	16.76	16.89	11.02

For the selected freeway corridor, the percentage reduction in average delay per vehicle indicates that the delay reduces by 40% for the low-traffic volume level compared to the base scenario. Similarly, the delay reduces by 40.68% and 34.74% for Sc12 in the northbound and southbound directions, respectively for peak traffic volume. The reduction in delay is lower for high-traffic volume scenarios compared to other scenarios. Notably, the percentage reduction is significantly higher for Sc5 compared to Sc4, indicating that the delay reduces significantly after the introduction of Level 3 and higher level CAVs. From Sc5 to Sc8, the percentage reduction in delay increases significantly with an increase in the penetration of CAVs. After Sc8, the improvements are negligible, highlighting that the effect of CAVs on delays is stabilized.

For the selected arterial street, the percentage reduction in the delay is less compared to the selected freeway corridor. Based on their characteristics, the intersections add a component of control delay (deceleration delay + stop time + acceleration delay) to the total delay. As a result, the delay values are higher for the selected arterial street. Moreover, due to the lower speed limit of the selected arterial street, the percentage reduction in delay is less compared to the selected freeway corridor. Table 8 indicates that the percentage reduction in delay for the selected arterial street varies from 11.02% to 40.71% for high-traffic volume Sc12. Unlike in the case of the selected freeway corridor, the percentage reduction increases from Sc8 to Sc12, indicating that the percentage reduction in delay significantly increases at a higher penetration of Level 3, Level 4, and Level 5 CAVs.

CAVs can travel faster (more towards the speed limit) than HDVs while maintaining smaller headway. As a result, the effect of CAVs is prominent on the delay. Intersections, either signalized or uncontrolled, along the arterial streets, result in frequent shockwave formation. The characteristics of a shockwave (shockwave speed and area) depend on the type of intersection and its characteristics. Therefore, due to the continuous formation of shockwaves along arterial streets, the reduction in delay for arterial streets is expected to be lower than for freeways.

5.3. Effect of CAVs on Buffer Time

As discussed previously, CAVs lead to more stable and certain travel times (figures 5 and 6); therefore, a significant effect of CAVs on travel time reliability is apparent. This study considers buffer time as a travel time reliability measure. Buffer time per mile is computed for each scenario using Equation 4.

$$Buffer\ time\ = \frac{95^{th} percentile\ TT - Average\ TT}{Length\ of\ corridor} \tag{4}$$

For a given scenario, the results (travel time) of three traffic volume levels are aggregated to estimate the buffer time. The estimated buffer time for each scenario, for the selected freeway corridor and arterial street, is shown in Figures 7 and 8.

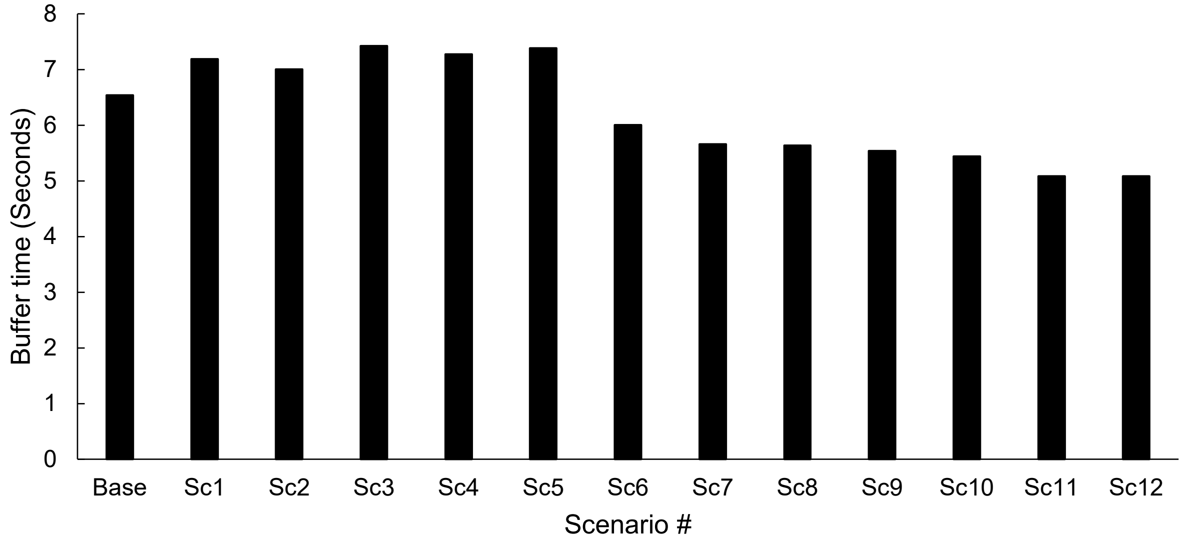


Figure 7. Variation in buffer time for the selected freeway corridor in Charlotte

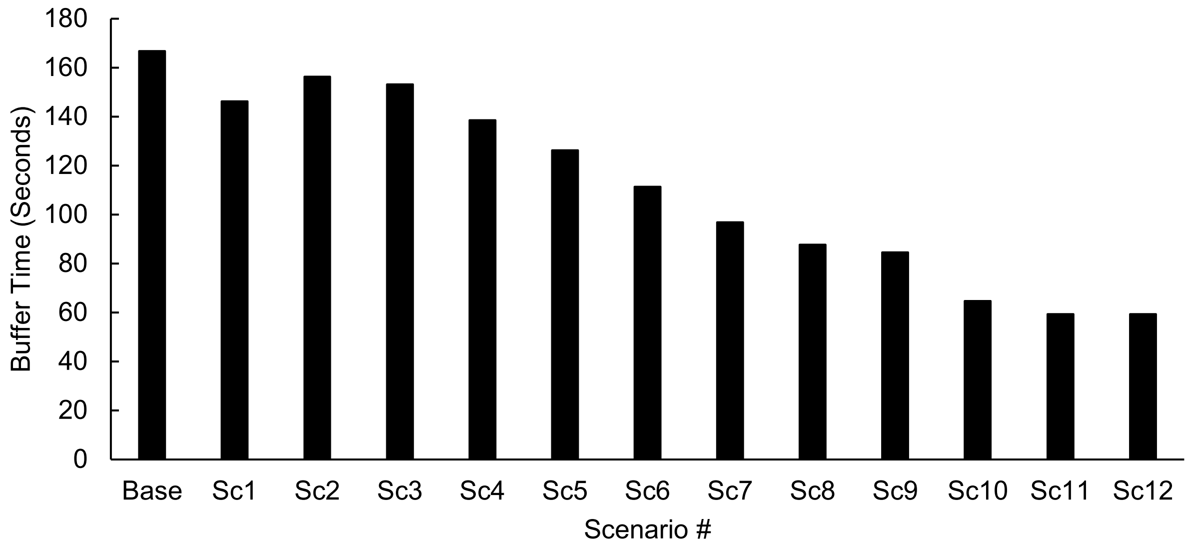


Figure 8. Variation in buffer time for the selected arterial street in Charlotte

Figure 7 shows that the buffer time decreases from Sc5. However, the buffer time fluctuates from Sc1 to Sc4. It is noticeable that there is a sudden reduction in buffer time from Sc5 to Sc6, primarily because in Sc6 and after, HDVs are replaced with CAVs. For the selected arterial street, the value of buffer time is significantly larger compared to the selected freeway corridor, primarily because of multiple signals along the corridor. The buffer time gradually decreases from 166 seconds to 59 seconds from the base scenario to Sc12. The reduction in buffer time is linear after Sc3. However, there is a slight increment in buffer time between Sc2 and Sc3, primarily because of heterogeneity due to HDVs, and Level 1, Level 2, and Level 3 CAVs.

Buffer time indicates the extra time the motorists consider planning to reach their destination on time. The reduction in buffer time for freeways and arterial streets indicates that travelers under CAVs conditions need lower buffers to reach their destination on time. This reduction in buffer time indicates reduced out-of-pocket costs for users due to saving in travel times.

Overall, a significant benefit in terms of reduction in travel times, delays, and buffer times can be expected with the increased penetration of CAVs. The reduction in travel times, delay, and buffer times for a traffic volume level is jointly influenced by the penetration of CAVs and the level of CAVs. Moreover, the operational benefits vary by the road functional class.

5.4. Effect of CAVs on Traffic Safety

Researchers used traffic conflicts to evaluate the effect of CAVs on traffic safety. A threshold value of 1.5s and 5s for TTC and post-encroachment time (PET) were adopted to estimate traffic conflicts. CAVs are expected to maintain smaller distances from other vehicles, accelerate faster, and achieve stable following conditions even at higher speeds. Therefore, the thresholds for identifying conflicts should vary for HDVs and CAVs. Using the same threshold value (i.e., TTC≤1.5s or PET≤5s) to evaluate the effect of CAVs on traffic safety could lead to biased conclusions. Traffic conflicts are regular observable events and provide (a) insights into the crash mechanism and (b) information regarding unsafe events, therefore, assisting with the development of an association between driving behavior and crash risk (Gore et al., 2023). Traffic conflicts can be extended to establish an association with crashes with a reasonable degree of accuracy. Researchers have employed the EVT to estimate crash risk using traffic conflicts (Arun et al., 2021, Ali et al., 2022; Zheng et al., 2014). Since EVT can extrapolate risk from observed (traffic conflicts) to unobserved levels (crashes), its application is potentially well suited to assess the effect of emerging vehicle technologies like CAVs on traffic safety. Therefore, an EVT approach is adopted in this study.

5.4.1. Extreme Value Theory (EVT)-based Safety Assessment

An EVT approach was used to estimate the safety benefits of CAVs. The EVT approach enables extrapolation from the observed levels (traffic conflicts) to unobserved levels, thereby enabling the prediction of rare events, such as crashes, from regularly observable events like traffic conflicts (Arun et al., 2021). POT and Block Maxima (BM) are two fundamental approaches to model extremes and perform EVT analysis. In the BM approach, observations are grouped into blocks (temporal or spatial blocks or both), and the maximum value of each block is treated as an extreme and modeled using Generalized Extreme Value (GEV) distribution. In the POT approach, the extremes are identified over a predefined threshold and are modeled using the Generalized Pareto (GP) distribution. The BM approach adopts extreme values within a given block, which may not truly represent the extreme values (Coles, 2001).

Therefore, the BM approach suffers from inefficient data utilization. However, the POT approach uses the entire dataset and, therefore, is efficient compared to the BM approach (Zheng et al., 2014). The detailed literature review on the application of EVT for crash risk estimation is presented in Ali et al. (2023), and interested readers are suggested to refer to the same.

5.4.2. Surrogate Safety Assessment Model (SSAM) and Traffic Conflict Indicator

SSAM was employed to extract simulated conflict data for different scenarios from the trajectory files generated from VISSIM (FHWA, 2008). TTC is the most commonly used indicator for traffic conflict-based crash estimation, and the same was used in this study. Mathematically, TTC is expressed as:

$$TTC = \frac{X_{LV} - X_{FV} - D_{LV}}{v_{FV} - v_{LV}};\ \forall\ (v_{FV} - v_{LV}) > 0 \qquad (5)$$

where X_{LV} and X_{FV} are the positions of the lead and the following vehicle at the time of the observation, D_{LV} is the length of the leading vehicle, and v_{FV} and v_{LV} are the speed of the leading and the following vehicle at the time of the observation. The TTC is developed on the assumption that two conflicting vehicles should maintain their constant velocity on the same path.

TTC for two conflict types, mainly rear-end (angle <=35°) and lane-change (angle >35° but <= 85°), were computed using the SSAM. Traffic conflicts were identified from the vehicle interactions when the interaction was characterized by TTC<3s (Hussain et al., 2022). This enabled elimination of the right tail of the distribution and the conflict extremes can only be identified from the left tail of the distribution, ensuring that identified extremes are the ones of interest for crash risk estimation.

5.4.3. Univariate Peak-over Threshold (POT) Model

Let $X_1, X_2, \ldots\ldots\ldots\ldots X_n$ be a set of independent random observations with identical distribution function F. The distribution function of exceedances $Y = X - u$ conditional upon $X > u$ is expressed as:

$$F_u(y) = 1 - P(X > u + y | X > u) \qquad (6)$$

For a large enough threshold u, the distribution function F(y) converges to GP distribution, which is expressed as:

$$G(y, \sigma, \xi) = \begin{cases} 1 - \left(1 + \frac{\xi y}{\sigma}\right)^{-\frac{1}{\xi}} & \xi \neq 0 \\ 1 - \exp\left(-\frac{y}{\sigma}\right) & \xi = 0 \end{cases} \qquad (7)$$

Defined on $\{y: Y > u\ and\ 1 + \frac{\xi y}{\sigma} > 0\}$, where $\sigma > 0$ is the scale parameter; $-\infty < \xi < \infty$ is the shape parameter.

The crash risk can be obtained from the GP distribution of the traffic conflict extremes (Songchitruksa and Tarko, 2006). For a traffic conflict measured by TTC, a smaller TTC value indicates a higher risk that a vehicle interaction will result in a crash, and the crash occurs when $TTC \leq 0$. The CR can be calculated from the fitted GP distribution of negated TTC (Songchitruska and Tarko, 2006) and is expressed as:

$$CR = \Pr(y \geq 0) = 1 - G(0) = \begin{cases} \left(1 - \frac{\xi u}{\sigma}\right)^{-\frac{1}{\xi}} & \xi \neq 0 \\ 1 - \exp\left(-\frac{u}{\sigma}\right) & \xi = 0 \end{cases} \tag{8}$$

where CR is the crash risk and y is the negated TTC.

It is essential to mention that CR is non-negative and is viewed as the number of crashes corresponding to the traffic conflict observation period t. Assuming that the traffic conflict observation period t is representative of a longer period of interest T, the expected number of crashes for T can be computed using:

$$N_t = \frac{T}{t} * CR \tag{9}$$

where N_c is the estimated number of crashes for a particular conflict type.

5.4.4. Threshold Selection

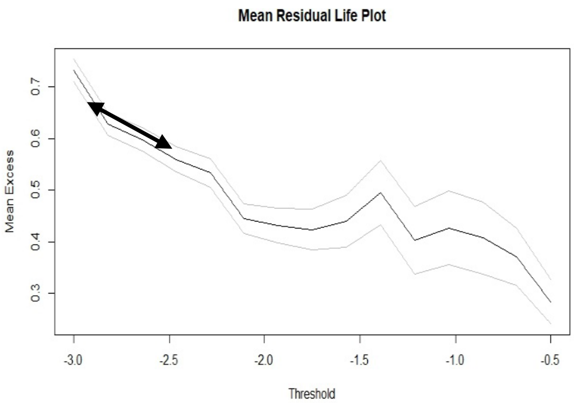
The selection of an appropriate threshold is pivotal for fitting the GP distribution because the GP is only valid for approximating the unknown distribution of extremes in asymptotic cases (Arun et al., 2022). Therefore, choosing a low threshold for modeling extremes will violate asymptotic assumptions. In contrast, a high threshold will lead to inadequate exceedances for modeling (Coles, 2001). Generally, the mean residual life (MRL) and threshold stability (TS) plots are adopted to identify the threshold values, and the same is adopted in this study.

If the GP distribution is valid for threshold exceedance u_o, then it should be equally valid for excesses over all thresholds $u > u_o$ subject to the appropriate change in the scale parameter σ_u (Coles, 2001), and the shape parameter is independent of the threshold. Therefore, $u > u_o$ the mean of threshold excess $E(x - u|x > u)$ is a linear function of u, and the MRL plot should be linear above the appropriate threshold. The threshold stability plot checks that in case the GP approximation is valid for threshold exceedances over u_o, then the reparametrized scale parameter $\sigma^* = \sigma_u - \xi_u$ and the shape parameter ξ are both constant for any threshold $u > u_o$ after allowing for variability due to sampling errors. Therefore, the MRL and TS plots can be used as a guide to selecting a suitable threshold. The final threshold was iteratively obtained through improvement in Akaike Information Criteria (AIC) (Arun et al., 2022). The threshold corresponding to the smallest AIC value is considered the best.

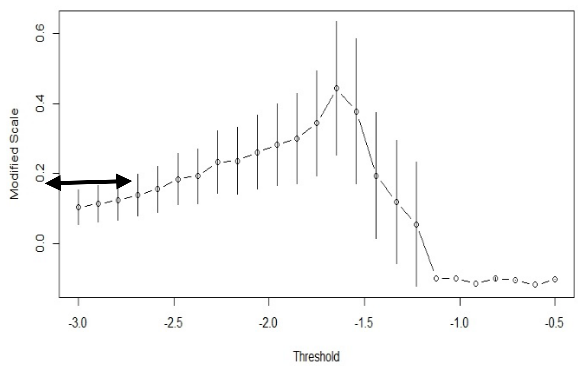
The POT models are sensitive to clustered data. The inherent assumption that extreme events are independent is violated if conflicts are serially dependent. Zheng et al. (2014)

reported that serial dependency should be dealt with in EVT. In this study, conflicts reported within 1-minute were checked for their link and vehicle ID. If vehicle IDs are found to be identical, those were considered dependent, and the minimum TTC value was considered (Wang et al., 2018).

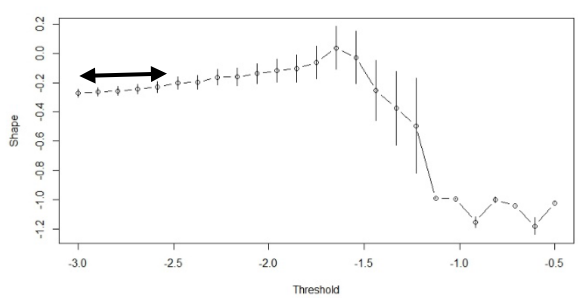
The selection of a suitable threshold is a prerequisite for estimating GP models. As discussed earlier, the MRL and TS plots were used to identify the threshold value. The MRL plot and TS plot for rear and lane change conflicts for the base scenario are illustrated in Figure 9. Here, plots for the selected freeway corridor in Charlotte are shown as an example.



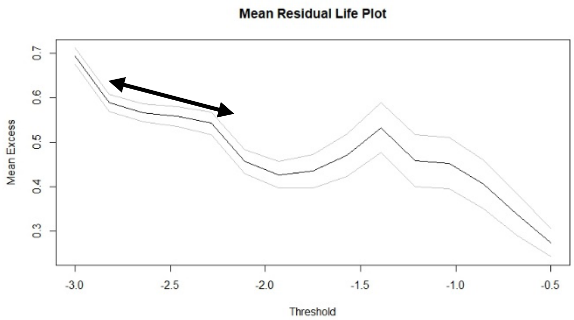
(b) Mean residual life (MRL) plot (RE)



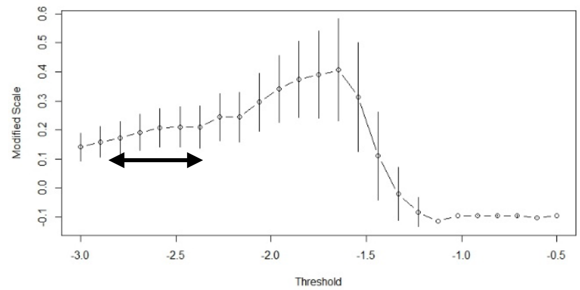
(b) Threshold stability plot (RE)



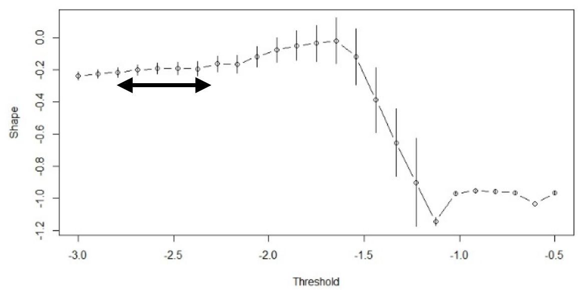
(c) Threshold stability plot (RE)



(d) Mean residual life (MRL) plot (LC)



(e) Threshold stability plot (LC)



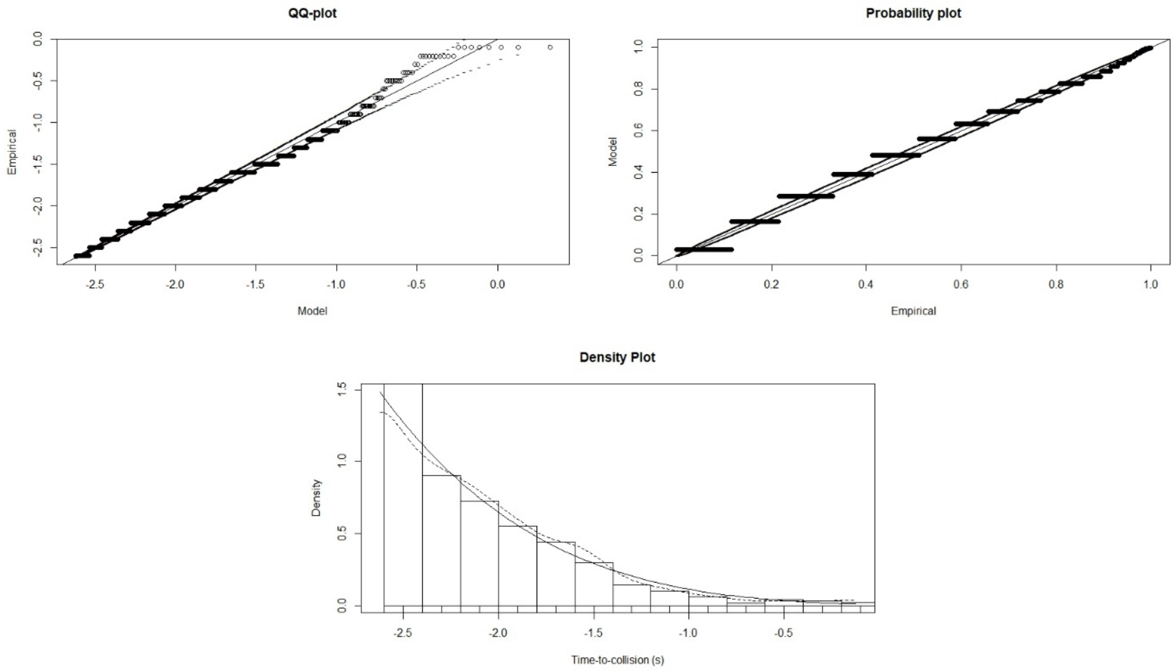
(e) Threshold stability plot (LC)

Figure 9. Mean residual life (MRL) and threshold stability plots for rear-end and lane change conflicts

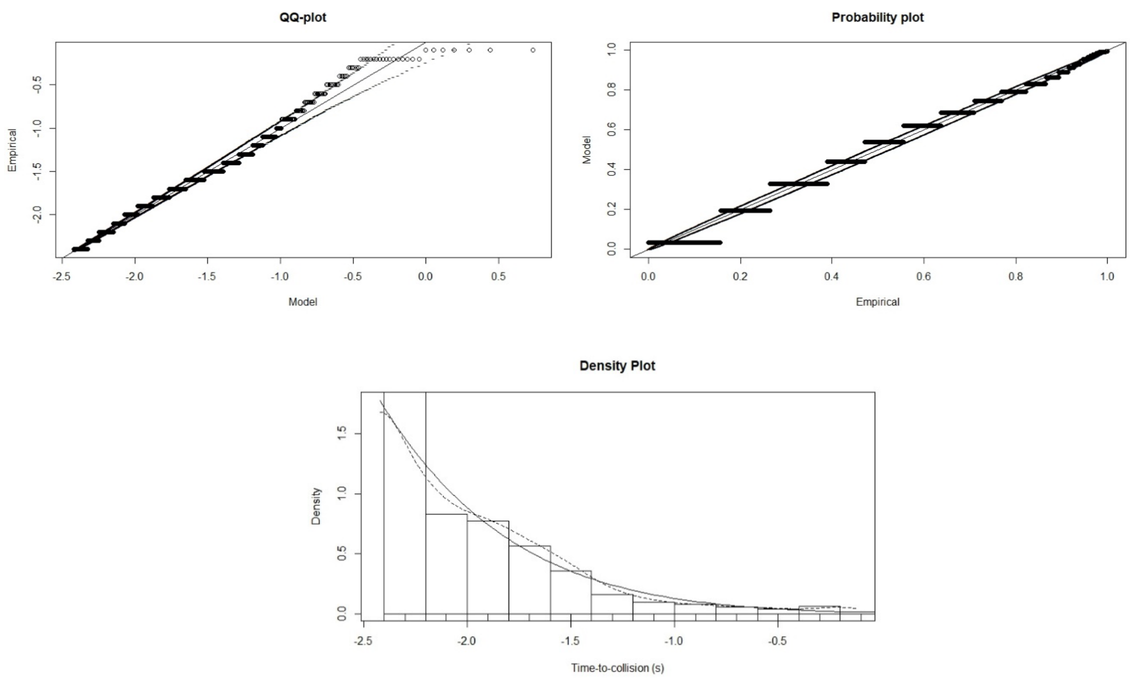
Note: RE: Rear-end Conflicts; LC: Lane Change Conflicts

For rear-end conflicts, the MRL plot appears linear (Figure 9a) when the negated TTC value is between -2.85 and -2.40. The corresponding modified scale and shape parameter plots (Figures 9b and 9c) seem stable in the range of -2.75 to -2.50. Similarly, for lane change conflicts, the MRL plot was observed to be linear for negated TTC value in the range of -2.75 to -2.35. The modified scale and shape plot were stable from -2.65 to -2.40. Therefore, the initial range of thresholds for the rear-end and lane change conflicts were inferred as (-2.70, -2.50) and (-2.65, -2.40). As discussed earlier, the final threshold value was iteratively obtained based on the AIC criteria. The final threshold values of -2.62s and -2.42s were derived for the rear-end and lane-change conflicts, respectively. For the derived threshold value, PP, QQ, and density plots, as shown in Figure 10, were developed to evaluate the goodness of fit of the GP distribution. This was done to conclude the appropriateness of the derived threshold value.

Figure 10 shows that the identified extreme (threshold) for rear-end and lane-change conflicts follow the GP distribution, highlighting the appropriateness of the identified threshold value.



(a) Rear End Conflicts



(b) Lane change conflicts

Figure 10. Goodness-of-fit plots

5.5. Effect of CAVs on Crash Risk

To estimate the effect of CAVs on traffic safety, univariate GP models were fitted to the thirteen CAVs scenarios using the methodology as explained earlier. The model fit results for the selected freeway corridor and arterial street in Charlotte are summarized in Table 9. The thresholds resulted in the shape parameter values of $\xi > -0.5$, ensuring the regular asymptotic properties of the MLEs (Smith, 1985). The number of crashes are estimated using Equation (9) for each scenario, and the results are summarized in Tables 9 and 10.

Table 9. Univariate GP model summary for different scenarios for the selected freeway corridor in Charlotte

Scenario #	Rear End				Lane Change			
	u	σ	ξ	N_t	u	σ	ξ	N_t
Base	-2.620	0.675	-0.173	2.327	-2.420	0.564	-0.098	5.797
Sc1	-2.620	0.643	-0.155	2.342	-2.515	0.594	-0.093	6.923
Sc2	-2.620	0.669	-0.190	1.130	-2.320	0.558	-0.104	6.326
Sc3	-2.620	0.657	-0.190	0.832	-2.410	0.529	-0.088	5.978
Sc4	-2.700	0.665	-0.198	0.764	-2.415	0.570	-0.104	5.649
Sc5	-2.620	0.656	-0.194	0.650	-2.630	0.604	-0.149	1.710
Sc6	-2.620	0.605	-0.164	0.835	-2.715	0.599	-0.154	0.681
Sc7	-2.430	0.618	-0.206	0.450	-2.810	0.633	-0.173	0.315
Sc8	-2.520	0.582	-0.169	0.546	-2.810	0.643	-0.177	0.344
Sc9	-2.335	0.584	-0.192	0.725	-2.810	0.656	-0.186	0.276
Sc10	-2.145	0.569	-0.239	0.095	-2.810	0.655	-0.191	0.185
Sc11	-2.145	0.605	-0.267	0.023	-2.810	0.623	-0.159	0.523
Sc12	-2.145	0.605	-0.267	0.023	-2.145	0.605	-0.267	0.523

Table 10. Univariate GP model summary for different scenarios for the selected arterial street in Charlotte

Scenario #	Rear End				Lane Change			
	u	σ	ξ	N_t	u	σ	ξ	N_t
Base	-1.300	0.280	-0.120	1.646	-1.300	0.360	-0.170	5.411
Sc1	-1.300	0.270	-0.130	0.758	-1.400	0.380	-0.180	3.459
Sc2	-1.300	0.290	-0.130	1.755	-1.400	0.380	-0.170	4.463
Sc3	-1.300	0.290	-0.140	1.260	-1.300	0.340	-0.130	7.385
Sc4	-1.300	0.280	-0.130	1.184	-1.300	0.380	-0.190	5.817
Sc5	-1.300	0.280	-0.130	1.184	-1.300	0.350	-0.170	4.116
Sc6	-1.300	0.280	-0.150	0.516	-1.300	0.330	-0.160	2.907
Sc7	-1.300	0.290	-0.180	0.157	-1.300	0.320	-0.170	1.470
Sc8	-1.200	0.270	-0.170	0.368	-1.300	0.330	-0.180	1.532
Sc9	-1.300	0.350	-0.240	0.140	-1.300	0.310	-0.170	0.947
Sc10	-1.200	0.300	-0.220	0.095	-1.280	0.300	-0.180	0.436
Sc11	-1.200	0.290	-0.220	0.025	-1.200	0.330	-0.240	0.272
Sc12	-1.200	0.290	-0.220	0.025	-1.200	0.330	-0.240	0.272

Tables 9 and 10 show that the expected number of rear-end and lane-change crashes reduces as the penetration of CAVs increases. A higher reduction in crashes can be observed when the penetration of Level 3 and higher level CAVs increases. The analysis revealed that the number of rear-end crashes reduced by 51% to 99%, whereas lane-change crashes reduced by 71% to 97% for the selected freeway corridor. However, the number of rear-end crashes reduced by 23% to 98%, whereas the number of lane-change crashes reduced by 18% to 95% for the selected arterial street. These findings are consistent with those reported by Papadoulis et al. (2019) and Yang et al. (2020). However, for certain scenarios, the number of rear-end and lane-change crashes increased, highlighting the deleterious effect of CAVs on traffic safety. The increase in crash risk ranged from 2% to 20% for rear-end crashes and 5% to 36% for lane change crashes. The uncertainty in the interaction between HDVs and CAVs increases crash risk.

Overall, it can be inferred that (a) CAVs bring about compelling benefits to road safety (reduction in crash risk), (b) safety benefits are higher when the penetration of Level 4 and Level 5 CAVs increases, which can be attributed to (a) stable following conditions and (b) cooperative lane change (Talebpour and Mahamassani, 2016; Ali et al., 2022, Nazir et al., 2023), and (c) reduction in crash risk also varies by the road functional class. The significant reduction in travel times and crashes is expected to bring economic benefits. The effect of CAVs on the economy is explained in the next subsection.

5.6. Economic Impact of CAVs

The cost of buffer time and crash cost for freeways and arterial streets are evaluated to quantify the economic impact of CAVs.

5.6.1. Buffer Time Cost

As mentioned earlier, using equation 4, the buffer time was estimated for each scenario. The buffer time index is mathematically expressed as the ratio of buffer time to average travel time. Once the buffer time is estimated, the cost of buffer time is computed using the generalized cost of buffer time reported by Pulugurtha et al. (2017). The generalized value of buffer time per minute for North Carolina is $0.45 for 2015 (Pulugurtha et al., 2017). Since the simulation model is developed using 2019 data, the buffer time cost in 2019 is estimated using Equation 10.

$$PV = \frac{FV}{(1+i)^t} \tag{10}$$

where PV = present value of the buffer time cost; FV = future value of the buffer time cost; i = inflation rate; t = years (where, t=0 for base year 2017)

Considering the inflation rate of 3% for North Carolina and the time difference of four years (2015 to 2019), the estimated cost of buffer time per minute for North Carolina in 2019 is $0.51. Considering the estimated cost per minute, the cost of buffer time per minute per mile is estimated for the selected freeway corridor and arterial street. The results are summarized in Table 11.

Table 11. Cost of buffer time per vehicle per mile for the selected freeway corridor and arterial street in Charlotte

Scenario #	Freeway			Arterial		
	Buffer time	Buffer time index	Cost of buffer time	Buffer time	Buffer time index	Cost of buffer time
Base	6.538	9.110	$0.055	166.790	64.903	$1.408
Sc1	7.186	10.012	$0.061	146.290	58.505	$1.235
Sc2	7.001	9.783	$0.059	156.370	62.866	$1.320
Sc3	7.423	10.404	$0.063	153.170	61.945	$1.293
Sc4	7.273	10.293	$0.061	138.600	56.399	$1.170
Sc5	7.381	10.596	$0.062	126.230	51.951	$1.066
Sc6	6.002	8.793	$0.051	111.410	46.443	$0.940
Sc7	5.657	8.369	$0.048	96.870	40.995	$0.818
Sc8	5.638	8.429	$0.048	87.740	38.013	$0.741
Sc9	5.539	8.328	$0.047	84.650	37.360	$0.715
Sc10	5.443	8.205	$0.046	64.730	29.344	$0.546
Sc11	5.083	7.659	$0.043	59.410	27.191	$0.501
Sc12	5.083	7.659	$0.043	59.410	27.191	$0.501

Note: The values of the buffer time index are in percentage.

The cost of buffer time per vehicle per mile varied for the selected freeway corridor and arterial street. For the base scenario, the cost of buffer time per vehicle per mile for the selected freeway corridor is $0.055. However, it is $1.41 per vehicle per mile for the selected arterial street. The cost of buffer time decreased with increasing penetration of CAVs for both corridors. The buffer time cost for the selected arterial street reduced from $1.41 in the base scenario to $0.50 in Sc11 and Sc12. For the selected freeway corridor, the cost of buffer time per vehicle per mile decreased from $0.055 to $0.043. The reduction in the cost of buffer time indicates that the economic benefits of CAVs in terms of buffer time would be higher for arterial streets compared to freeways.

5.6.2. Crash Cost

In addition to travel time savings, CAVs could reduce crash costs. From the estimated number of crashes for each scenario, crashes per mile were obtained for freeways and arterial streets to quantify the economic impacts of CAVs on crash costs.

Since the base scenario was developed for 2019, crash costs for rear-end and lane change crashes were used as per 2019 Standardized Crash Cost Estimates for North Carolina (NCDOT, 2019). Since the cost for a particular lane change crash is not specified, the average crash cost is used for lane change crashes. However, for rear-end crashes, the average rear-end crash cost is used. The results of variation in crash costs per mile for freeways and arterial streets for each scenario are summarized in Table 12.

Table 12. Crash cost per mile of the selected freeway corridor and arterial street in Charlotte

Scenario #	Freeway		Arterial	
	Rear-end	Lane change	Rear-end	Lane change
Base	$27,087	$168,697	$45,941	$377,558
Sc1	$27,262	$201,465	$21,156	$241,355
Sc2	$13,154	$184,092	$48,983	$311,410
Sc3	$9,685	$173,965	$35,167	$515,296
Sc4	$8,893	$164,390	$33,046	$405,887
Sc5	$7,566	$49,762	$33,046	$287,198
Sc6	$9,720	$19,818	$14,402	$202,839
Sc7	$5,238	$9,167	$4,382	$102,571
Sc8	$6,356	$10,011	$10,271	$106,897
Sc9	$8,439	$8,032	$3,907	$66,078
Sc10	$1,106	$5,384	$2,651	$30,422
Sc11	$268	$15,220	$698	$18,979
Sc12	$268	$15,220	$698	$18,979

The cost of rear-end crashes per mile length for the selected freeway corridor in the base scenario is estimated to be $27,087. It decreased with the increasing penetration of CAVs and is equal to $268 in Sc11 and Sc12. Similarly, the cost of lane change crashes decreased from $168,697 in the base scenario to $15,200 in Sc11 and Sc12. On the selected arterial street, the variation is similar to the selected freeway corridor as the cost of rear-end crashes per mile length is reduced from $45,941 to $698. The crash cost for lane change crashes on the selected arterial street is highest for the base scenario ($377,558). However, it reduced to $18,979 in Sc12, indicating huge savings in crash cost per mile length. The reduction in crash costs for the selected freeway corridor and arterial street is significant from Sc6 to Sc7, indicating that once all the HDVs are replaced with CAVs, the economic impacts will be higher for arterial streets and freeways.

6. Conclusions

The recent advancements in technology and vehicular automation are expected to bring numerous changes to the transportation system. The CAVs are expected to integrate into the existing transportation system through six levels of automation. Each level of CAV is expected to enhance operational and safety performance compared to HDVs. HDVs and different levels of CAVs are expected to coexist for a considerable time. As a result, heterogeneous traffic flow conditions are expected. The heterogeneity in traffic flow results in the varying performance of these vehicles at varying penetration rates. This study quantifies the effect of a mix of vehicles with different levels of automation on operations, safety, and the economy of freeways and arterial streets in North Carolina.

A literature review was conducted to identify the most appropriate analysis method to identify the effect of CAVs on different aspects of transportation systems. Study authors identified the microsimulation approach using PTV Vissim as the most suitable technique for modeling CAVs as it provides detailed results, including vehicle trajectories and flexibility to model vehicles with different driving behaviors.

The study authors developed microsimulation models for freeway and arterial streets links in Charlotte and freeway links in Raleigh. Details related to road geometry, traffic volume, signal timings, turning movements, and speed limit were incorporated into the networks. The developed simulation model was calibrated for travel time and traffic volume by optimizing the driving behavior parameters to mimic the exact traffic conditions in the network. The study authors also conducted a sensitivity analysis to determine the sensitive driving behavior parameters and an iterative procedure was used to optimize the Weidemann99 driving behavior parameters.

To mimic the behavior of vehicles with different levels of automation, driving behavior parameters were identified from the existing literature. Thirteen scenarios were developed with varying penetration of different levels of CAVs considering the existing trends in crash data for Level 1 and Level 2 CAVs and forecasted penetrations for different levels of CAVs in the existing literature. Further, this study considered three traffic volume levels for analysis, including current peak hour traffic volume, off-peak volume (half of the current peak hour traffic volume), and forecasted peak hour traffic volume for 2030. The study authors conducted five simulation runs using varying random seeds for the developed 39 scenarios (13 corresponding to CAV penetration rates and three traffic volumes). The results from 195 scenarios (13*3*5) for each corridor were further processed to quantify the effect of CAVs on operations, safety, and the economy.

Measures such as variation in travel time, the percentage reduction in travel time and delay per vehicle, and buffer time were estimated to quantify the effect of CAVs on the operational performance of traffic flow. This study used traffic conflicts to identify the effect of CAVs on safety. Vehicle trajectories for each scenario and demand level were extracted from the microsimulation models. The extracted vehicle trajectories were processed using the SSAM tool. The processed data contain information about the type of conflict and its corresponding

TTC values. This study employed an EVT-based POT approach to estimate crash risk and the number of crashes by crash type. The estimated crash risk and number of crashes were compared between scenarios to quantify the effect of CAVs on traffic safety.

The operational analysis and safety analysis results were used to quantity the impact of CAVs on the economy. More specifically, this study estimated buffer time and crash cost based on the values of buffer time and the number of crashes for each scenario and were compared.

Overall, the CAVs will have a significant impact on the existing transportation system of North Carolina by reducing travel time, delay per vehicle, number of crashes, cost of buffer time, and crash cost. However, the benefits will vary depending on the road functional class, different penetration levels of CAVs, and traffic volume. The findings provided in this study quantify the effect of CAVs on different aspects of the transportation system. The estimated crash costs per mile length of freeways and arterial streets corresponding to different CAVs penetration scenarios could be used to forecast the statewide impacts of CAVs. Similarly, the cost of buffer time per vehicle for different scenarios of CAV penetration could be adopted to forecast the statewide impact by using the estimated values of buffer cost and VMT. The key findings from this study are summarized next.

- For freeways, travel time per vehicle is estimated to reduce by 9.72% for current peak hour traffic volumes when the penetration of Level 5 CAVs is ~100%. The effect is expected to be higher in the case of peak-hour traffic demand than at forecasted peak or lower traffic volumes.
- On freeways, travel time per vehicle will drop significantly compared to the scenario with Level 1, Level 2, and Level 3 CAVs once Level 4 CAVs penetrate the market (Sc4).
- Travel time is estimated to reduce by up to 29.6% on arterial streets when Level 5 CAVs penetrate the system. The benefits in terms of travel time are higher for forecasted traffic volume compared to current peak and off-peak traffic volumes.
- The sudden reduction in travel time and delay is expected when the penetration of Level 2 and higher CAVs increases, with a simultaneous reduction in HDVs.
- The delay per vehicle on freeways is expected to reduce by ~40% with ~100% Level 5 CAVs, highlighting the significant benefits of CAVs in terms of operations. The benefits are higher for current peak-hour traffic volumes than lower or higher ones.
- On freeways, once all HDVs are replaced with CAVs (in Sc7), there is a sudden increment in delay reduction compared to the scenario with a mix of HDVs and CAVs.
- The delay per vehicle on arterial streets is estimated to reduce by 40.7% at ~100% penetration of Level 5 CAVs. The benefits in terms of per-vehicle delay reduction are higher during forecasted peak traffic volumes compared to current peak and off-peak hour traffic volumes.
- Similar to travel time results, the delay on arterial streets is expected to significantly reduce in scenarios when the penetration of Level 2 and higher level CAVs increases.
- The number of rear-end and lane change crashes on freeways is estimated to decrease with the increasing penetration of CAVs. The safety increases significantly compared to the scenario with a mix of HDVs and CAVs (Sc6) once all HDVs are replaced with different levels of CAVs (Sc7).

- The number of rear-end and lane change crashes is estimated to reduce with increasing penetration of different levels of CAVs on arterial streets. The number of crashes suddenly drops once Level 3 CAVs begin to penetrate.
- Rear-end and lane-change crashes are expected to reduce by ~90% when the penetration of Level 5 CAVS is ~100%. Similar results in terms of crash reduction can be expected for freeways and arterial streets.
- The increasing penetration of CAVs will significantly impact the crash cost per mile. The cost of rear-end crashes per mile under ~100% penetration of Level 5 CAVs is estimated to be $268 compared to $27,087 in current traffic conditions. The cost of lane change crashes per mile on freeways is estimated to reduce from $168,697 in the current traffic scenario to $15,220 for ~100% penetration of Level 5 CAVs.
- Increasing penetration of CAVs will greatly impact crash cost per mile. The cost of rear-end crashes per mile will reduce from $45,941 for the current traffic scenario to $698 for ~100% penetration of Level 5 CAVs. Meanwhile, the cost of lane change crashes per mile is estimated to reduce from $377,558 to $18,979.

7. Recommendations

This study serves as a framework for identifying the effect of CAV penetration on operations, safety, and the economy. The benefits of CAVs on operations, safety, and the economy of freeways and arterial streets are quantified in this study, and corresponding values of benefits are highlighted in the study results. The recommendations provided based on the study results are as follows.

1. CAVs are expected to enhance traffic operations and safety. However, the operational benefits of CAVs on freeways will be lower than those on arterial streets.
2. The benefits of CAVs in terms of freeway and arterial operations will increase significantly with increasing penetration of vehicles with Level 3 and higher automation.
3. The safety of freeways will significantly increase when CAVs replace all HDVs. However, the benefits will increase immediately after Level 3 and higher level CAVs begin to penetrate the transportation system on arterial streets.
4. The cost of buffer time per vehicle per mile estimated in this study for different CAV penetrations scenarios could be used to estimate statewide impacts based on VMT on each road functional class.
5. Statewide impacts of CAVs on safety and crash cost can be estimated based on the percentage reduction in crashes per mile for freeways and arterial streets and their associated crash cost.
6. Operational and safety effects are estimated to increase significantly with the increasing penetration of Level 4 and Level 5 CAVs. Therefore, it is necessary to upgrade the existing infrastructure to facilitate vehicle-to-infrastructure communication.

8. Implementation and Technology Transfer Plan

The products of this research are quantified values of percentage reduction in travel time, delay, and buffer time for freeways and arterials. Other useful products are estimated reduction in crashes corresponding to varying CAV penetration scenarios, cost of buffer time per vehicle per mile, and costs of rear-end and lane change crashes per mile.

NCDOT could use the simulated traffic models or findings from the simulated models to evaluate the operational performance of sample heterogeneous networks. Furthermore, the models developed can serve as the basis for validation and calibration of the operational performance before large-scale implementation of future transportation projects. The recommended cost of buffer time per vehicle per mile and crash costs could be used by NCDOT to forecast the statewide economic impacts in varying CAV penetration scenarios. The end product of the research could be used for formulating strategies and policies for designing CAV-inclusive transportation systems.

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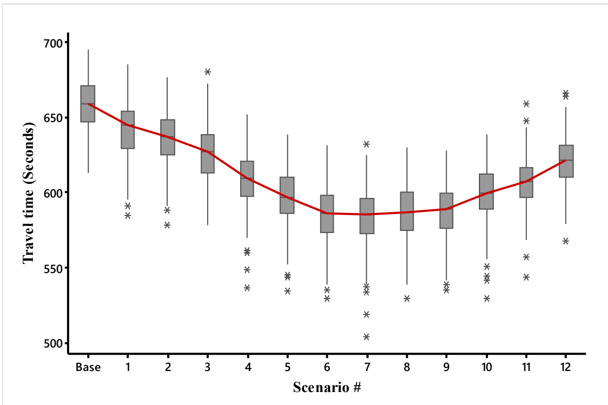
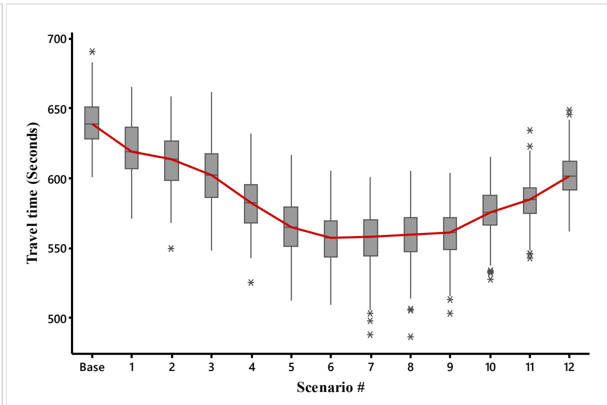
Appendix A: Raleigh Corridor Results

Operational Results

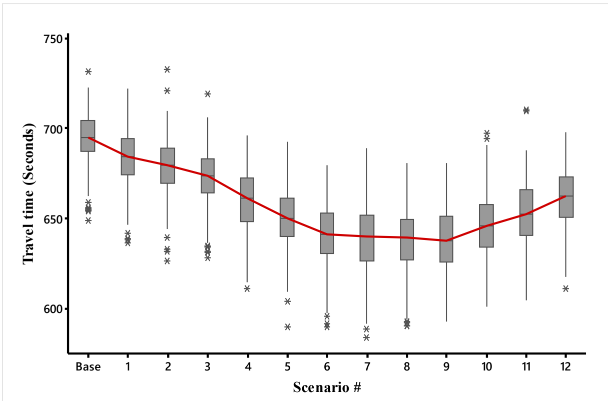
Variation in travel time on the selected freeway corridor in Raleigh is shown in Figure A-1.



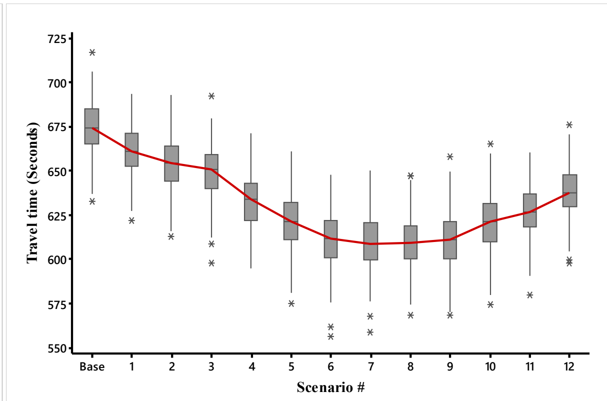
(c) Eastbound low traffic



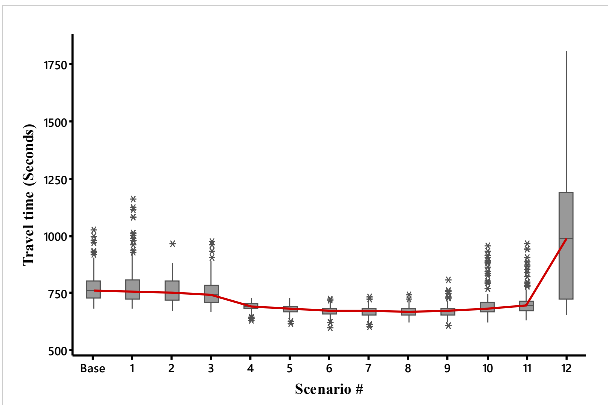
(b) Westbound low traffic



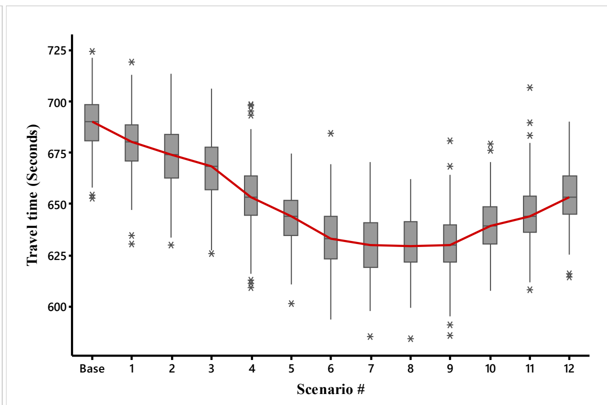
(d) Eastbound normal traffic



(d) Westbound normal traffic



(f) Eastbound high traffic



(f) Westbound high traffic

Figure A-1. Variation in travel time for the selected freeway corridor in Raleigh

The results summarized in Figure A-1 show that travel time per vehicle significantly varies with increasing penetration of CAVs. All the scenarios except high traffic (in eastbound direction) showed consistent results indicating that travel time decreases from the base scenario to Sc8. The reduction is higher from the base scenario to Sc6 but relatively lower from Sc6 to Sc8. However, after Sc8, the travel time per vehicle increased gradually until Sc12. The trend for the forecasted peak traffic volumes (in eastbound direction) is similar to those from the base scenario to Sc11. However, in Sc12, a sudden spike in travel time and a significant increment in travel time variability are observed. To quantify the reduction in travel time compared to base scenario, the percentage reduction in average travel time is estimated as shown in Table A-1.

Table A-1. Percentage reduction in travel time for the selected freeway corridor in Raleigh

Scenario #	Eastbound			Westbound		
	Low	Normal	High	Low	Normal	High
Sc1	2.47	1.64	-1.41	2.98	1.97	1.45
Sc2	3.43	2.35	1.18	4.18	2.96	2.42
Sc3	4.90	3.11	2.60	5.80	3.82	3.26
Sc4	7.54	4.98	10.54	8.93	6.17	5.28
Sc5	9.37	6.47	11.98	11.57	7.96	6.71
Sc6	11.05	7.76	13.16	12.89	9.34	8.12
Sc7	11.39	8.07	13.22	13.10	9.60	8.59
Sc8	10.96	8.20	13.25	12.66	9.63	8.55
Sc9	10.80	8.19	13.08	12.41	9.31	8.52
Sc10	8.90	7.01	9.61	9.83	7.90	7.22
Sc11	7.88	6.08	8.78	8.60	6.96	6.49
Sc12	5.76	4.72	-28.73	5.91	5.34	5.19

The results shown in Table A-1 indicate that travel time is expected to decrease by 13.25% in Sc8 for high-traffic conditions. After Sc8, the reduction in travel time compared to the base scenario is less, indicating that the value of travel time is higher for the remaining scenarios. Further, the percentage reduction is higher for high traffic conditions in the eastbound direction. In contrast, the percentage reduction in travel time in the westbound direction is higher for low traffic conditions.

The percentage reduction in average delay per vehicle is shown in Table A-2. The results summarized in Table A-2 show that the percentage reduction in delay per vehicle increased from 6.03% in Sc1 to 29.37% in Sc8 for low traffic conditions (in the eastbound direction). A similar trend is observed for all scenarios. After Sc8, the reduction in percentage delay decreases until Sc12. From the results, it is essential to note that all the values except for eastbound high traffic in Sc12 are positive, indicating improvement in terms of delay with increasing penetration of CAVs.

Table A-2. Percentage reduction in delay for the selected freeway corridor in Raleigh

Scenario #	Eastbound			Westbound		
	Low	Normal	High	Low	Normal	High
Sc1	6.63	4.03	-3.03	8.41	5.08	3.60
Sc2	9.19	5.79	2.54	11.79	7.63	6.03
Sc3	13.12	7.66	5.60	16.36	9.85	8.11
Sc4	20.19	12.27	22.70	25.19	15.89	13.15
Sc5	25.11	15.95	25.80	32.63	20.52	16.69
Sc6	29.60	19.11	28.33	36.36	24.06	20.20
Sc7	30.50	19.87	28.46	36.94	24.74	21.37
Sc8	29.37	20.20	28.53	35.69	24.80	21.28
Sc9	28.92	20.19	28.17	34.99	23.99	21.21
Sc10	23.84	17.27	20.70	27.72	20.35	17.96
Sc11	21.11	14.99	18.91	24.26	17.94	16.14
Sc12	15.42	11.64	-61.87	16.67	13.75	12.92

An economic impact analysis is conducted to quantify and forecast the benefits in terms of buffer time cost. The cost of buffer time per vehicle per mile length of the freeway, obtained from the operational results of the selected freeway corridor in Raleigh, is summarized in Table A-3.

Table A-3. Cost of buffer time per vehicle per mile for the selected freeway corridor in Raleigh

Scenario #	Freeways (Raleigh)		
	Buffer time	Buffer time index	Cost of buffer time
Base	8.367	10.596	0.071
Sc1	9.596	12.371	0.082
Sc2	8.292	10.801	0.070
Sc3	8.014	10.544	0.068
Sc4	5.592	7.533	0.048
Sc5	5.764	7.906	0.049
Sc6	5.953	8.291	0.051
Sc7	5.872	8.214	0.050
Sc8	5.756	8.043	0.049
Sc9	5.628	7.854	0.048
Sc10	7.176	9.850	0.061
Sc11	7.388	10.049	0.063
Sc12	23.358	31.244	0.199

The results show that the cost of buffer time decreases from $0.071 per vehicle per mile in the base scenario to $0.048 in Sc9. After Sc9, the cost of buffer time increases marginally in Sc10 and SC11. The buffer time cost is significantly higher in the case of Sc12 than in all other scenarios. Overall, the results for the Raleigh corridor follow a similar trend to those in Charlotte with a few exceptions.