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Assessing the Impact of Adverse Weather on Performance and Safety of Connected and Autonomous Vehicles

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Abstract

Connected and Autonomous Vehicles (CAVs) might significantly enhance the transportation system by improving safety, accessibility, efficiency, and sustainability. However, a major challenge lies in ensuring CAVs can operate properly under diverse weather conditions, which have already proven to impair human driving capabilities. This pioneering study aims to bridge a crucial research gap by comprehensively assessing the performance of CAVs on traffic operations and safety across varying weather scenarios. Using microscopic traffic simulation in VISSIM and the Surrogate Safety Assessment Model (SSAM), this study evaluates key metrics, including average speed, delay, number of stops, travel time, and number of conflicts for different CAV market penetration rates. The analysis spans 21 scenarios under clear, light rain, heavy rain, and foggy conditions within a selected urban corridor in the United Arab Emirates. The results showed that the average speed rose by 55% in clear weather, while the average delay, the number of stops, travel time, and the number of accidents decreased by 50%, 50%, 95%, and 68%, respectively. In light rain, the average speed improved by 43%, while the average delay, number of stops, travel time, and the number of accidents reduced by 43%, 56%, 96%, and 74%, respectively. The average speed increased by 82% under heavy rain, while the average delay, the number of stops, the travel time, and the number of accidents all fell by 62%, 68%, 96%, and 74%, respectively. In fog, the average speed rose by 32%, while the average delay, average stop number, travel time, and the number of accidents decreased by 33%, 47%, 90%, and 83%, respectively. Overall, this paper highlights the need for resilient CAV systems adaptable to diverse environmental conditions. It helps advance the understanding of how CAVs can be optimized for safety and efficiency in urban settings, contributing to sustainable transportation solutions. It provides insights into the challenges and innovative approaches for CAV deployment in adverse weather, laying a foundation for future research and the broader implementation of these technologies in urban mobility.

Keywords: CAV; Connected and Autonomous Vehicles; Road Safety; Traffic Operation; Urban Study; Urban Planning.

1. Introduction

Over the past decade, the rapid evolution of connected and automated vehicle (CAV) technologies has marked a significant transformation in the transportation sector. These technologies, equipped with advanced sensors, wireless communication capabilities, and sophisticated control algorithms, offer considerable potential for enhancing the safety, efficiency, and sustainability of road networks [1]. Despite these advancements, the integration of CAV technologies poses significant challenges, including interoperability issues with existing infrastructure, the high costs associated with their deployment, and the risks of cybersecurity breaches. As CAV technologies continue to develop and their

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application broadens, it becomes crucial to assess their performance in varied driving conditions, especially under adverse weather. Conditions such as heavy rain, snow, fog, and ice significantly challenge both human drivers and conventional vehicle systems by reducing visibility, impairing traction, and increasing stopping distances. These factors often lead to decreased road capacity, heightened accident risks, and traffic disruptions [2, 3]. The deployment of CAVs presents an opportunity to alleviate the negative impacts of such adverse weather on transportation systems. Nonetheless, these technologies still face substantial obstacles in adverse conditions due to the limitations of sensor capabilities and the requirement for highly adaptable decision-making algorithms that can respond to dynamic environmental changes.

Moreover, while CAVs are anticipated to demonstrate enhanced cooperative behavior, yielding greater systemic benefits compared to human-operated vehicles [4, 5], the empirical evidence regarding their impact on traffic flow remains limited. This is largely due to the ongoing development of their operational technologies and regulatory frameworks. A critical concern remains the assurance of safety and reliability. Although CAVs aim to reduce the incidence of human driving errors, which contribute to approximately 94% of traffic accidents [6, 7], their performance under adverse weather conditions remains largely unexplored. The challenge lies in ensuring these vehicles can safely operate without human oversight over functions such as steering, braking, acceleration, and road monitoring. The National Highway Traffic Safety Administration (NHTSA) has classified vehicle automation into six levels, each delineating a different degree of automation and presenting distinct challenges in technology and integration into existing traffic systems, as illustrated in Figure 1 [8].

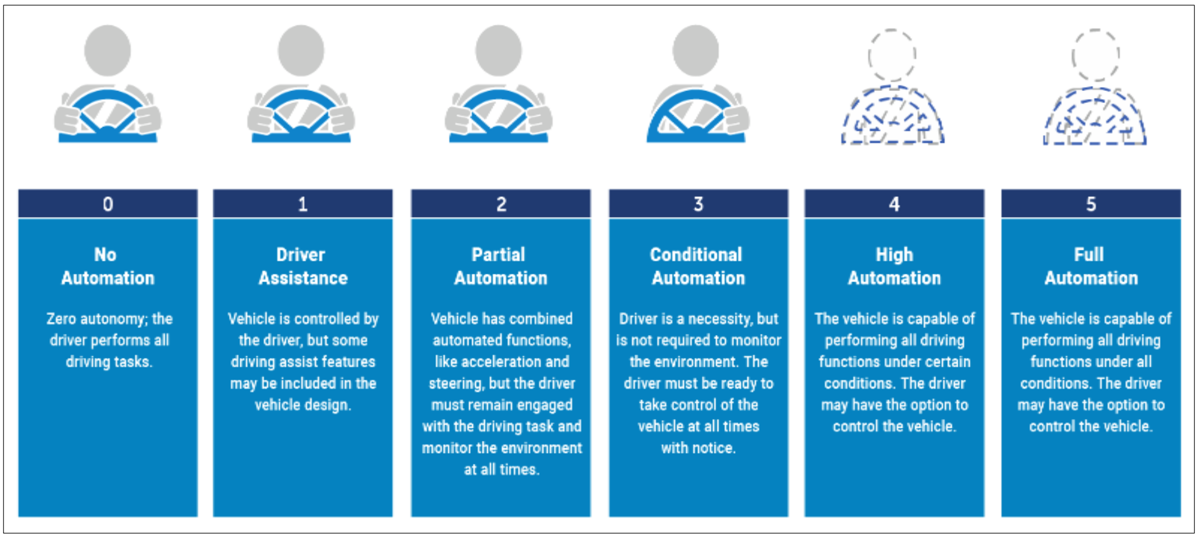


Figure 1. Automation levels (NHTSA)

This research is centered on fully automated vehicles, also known as Level 5 automation. Within this study, the term "autonomous vehicles" specifically refers to those with complete automation capabilities. Since the early 1950s, it has been recognized that weather patterns significantly influence driver behavior and traffic flow [9]. Adverse weather conditions notably affect traffic-related variables such as free-flow speed and capacity [10-12]. Furthermore, such conditions influence travelers' decisions regarding the mode of transport, route selection, timing, destination, and even the decision to travel at all. Consequently, weather conditions impact both the supply and demand aspects of the transportation sector. Studies show that adverse weather reduces service capacity and travel predictability while increasing the likelihood of accidents. It is estimated that adverse road conditions due to weather contribute to 28% of all highway collisions and 19% of all fatalities [13]. Therefore, the ability of CAVs to function effectively in adverse weather conditions, including rain, snow, and fog, is a critical concern.

To date, comprehensive research on the performance of CAVs under diverse weather conditions remains limited. The objective of this study is to investigate the potential impact of CAVs on traffic safety and operations across different weather scenarios, assuming optimal operational conditions free from system errors or cyberattacks. Such assumptions, common in preliminary studies, help in assessing the theoretical maximum benefits of CAV technology. The study sets out with the following specific aims:

- Create a detailed simulation model for CAVs that integrates algorithms for car-following, lane-changing, and other driving behaviors under varying weather conditions.
- Conduct simulations across various Market Penetration Rates (MPR) of CAVs to observe their performance under varying weather conditions.
- Assess the safety of simulated CAVs by analyzing conflicts within the traffic flow under varying weather conditions.

- Evaluate the operational efficiency of CAVs in the simulation, considering factors such as delay and speed under varying weather conditions.
- Compare the operational and safety outcomes between CAVs and conventional road vehicles (RVs) within the simulation framework under varying weather conditions.

This paper emphasizes the importance of developing resilient CAV systems that can adapt to a wide range of environmental conditions. Through this comprehensive study, we enhance our understanding of how autonomous vehicles can be optimized for safe and efficient operation across diverse urban settings. This research not only contributes significantly to the ongoing discussion about sustainable transportation solutions but also provides clear insights into the challenges and innovative solutions associated with deploying connected and autonomous vehicles in adverse weather conditions. Ultimately, this work lays a solid foundation for future research and technological advancements in the field of urban mobility, paving the way for broader adoption and implementation of CAV technologies.

The structure of this paper is organized as follows: In Section 2, the relevant literature is reviewed, and research gaps in the performance of CAVs in adverse weather conditions are identified. The applied methodology is outlined in Section 3, utilizing VISSIM simulations and the Surrogate Safety Assessment Model (SSAM). Results are presented in Section 4, focusing on the impacts of various weather conditions on CAV performance metrics. These findings are discussed in Section 5 in the context of existing research and their implications for urban planning and policy. Finally, the paper is concluded in Section 6 with a summary of our findings and suggestions for future research directions.

2. Literature Review

While the literature extensively covers the influence of CAVs on transportation networks, as well as the impact of adverse weather conditions on normal road safety and traffic flow, there remains a gap in research regarding the behavior of CAVs during adverse weather conditions. Previous studies have predominantly concentrated on how weather conditions affect (regular human driving) traffic flow characteristics [14–18]. For instance, Brilon and Ponzlet found that snow and rain decreased speeds by approximately 7 and 4 mph, respectively, on six-lane roads under uncongested and partially dense circumstances [14]. Smith et al. investigated the impact of varying rainfall intensities on highway capacity and operational rates [15]. They discovered that light rain (0.01 - 0.25 inches/hour) reduced freeway capacity by 4-10%, while heavy rain (0.25 inches/hour or more) decreased it by 25-30%. Additionally, regardless of intensity, rain led to an average speed reduction of 5.0–6.5%. Agarwal et al. utilized a four-year dataset comprising detector occupancy data and weather information to assess the effects of rain, snow, and pavement conditions on freeway traffic flow [19]. They observed that heavy rains (exceeding 0.25 inches/hour) and heavy snowfall (more than 0.5 inches/hour) resulted in capacity reductions of 10%-17% and 19%-27%, respectively, with speed decreasing by 4%-7% and 11%-15%. Similarly, Abdel-Aty et al. conducted a comprehensive investigation into traffic characteristics in foggy conditions [20].

Their findings indicated that reduced visibility caused a significant decline in speed and headway, with the standard deviation of speed and headway increasing compared to clear conditions. In recent years, scholarly interest has surged regarding the benefits that CAVs offer, as highlighted in studies [21–24]. To evaluate the efficiency of CAV technology, the research community has leaned on analyzing real-world CAV data or leveraging simulation techniques. The analysis of real-world data often includes studies from initiatives like the Safety Pilot Model Deployment, whereas simulations involve using specialized CAV simulation tools or traffic micro-simulation software. Given the nascent stage of CAV deployment, simulations have emerged as the dominant method for studying CAVs. An example of such research is by Kim et al., who explored the effects of CAV integration on freeway corridors in Virginia through simulations that incorporated a mix of Legacy Vehicles (LV), AV, and CAV [25].

Utilizing VISSIM for crafting models of driving behaviors for AVs and CAVs, researchers identified that the inclusion of AVs and CAVs led to an increase in road capacity by 29% and 91%, respectively, within a basic freeway testing environment. In scenarios involving freeway merges, the presence of AV and CAV technology was found to boost road capacity by 48% and 60%, respectively. Moreover, several studies have applied traffic micro-simulation tools like the Surrogate Safety Assessment Model (SSAM) provided by the Federal Highway Administration (FHWA) to assess the safety impacts of Connected and Autonomous Vehicles (CAVs) [24–29]. These studies have utilized dual-stage calibration processes, yielding encouraging results. Nevertheless, the exploration of micro-simulation's utility in evaluating CAV safety remains relatively underexplored. For instance, Papadoulis et al. designed a decision-support algorithm for the control of CAVs through the External Driver Model API in VISSIM. This algorithm enabled the longitudinal control, the monitoring of nearby vehicles, the identification of surrounding CAVs, and the execution of lateral manoeuvres adhering to freeway traffic management principles [29].

Assessment of this algorithm with SSAM highlighted a notable enhancement in road safety attributable to CAV implementation, observable even at minimal market penetration levels. Specifically, reductions in forecasted traffic conflicts were recorded at 12-47%, 50-80%, 82-92%, and 90-94% for CAV market penetrations of 25%, 50%, 75%, and 100%, respectively. investigated the effects of varying AV sharing ratios at different speeds on signalized intersection management, using TRANSYT and Vissim simulations [30]. Findings indicate that higher AV shares enhance traffic flow by optimizing traffic light timing, with the most effective flow occurring at a 100% AV share. Conversely, lower AV percentages disrupt traffic patterns. Additionally, traffic simulations at 20 km/h and 60 km/h present challenges, while speeds between 30 and 50 km/h in urban settings yield the most stable and predictable results. A study utilized traffic simulation to assess the impact of AVs on delay times between origin and destination (OD) [31]. They found that the integration of AVs notably alters traffic flow, with improvements becoming significant as the market penetration rate (MPR) of these vehicles increases. Ahmed et al. evaluated the cumulative-anticipative car-following (CACF) model for CAVs using VISSIM simulations, comparing it with traditional and cooperative adaptive cruise control (CACC) models [32]. The CACF model shows improved traffic throughput, reduced delays, and better travel times, especially effective in preventing traffic shockwaves and bottlenecks.

Limited studies have investigated the impacts of CAVs and AVs on traffic systems, with a specific focus on safety performance under different weather conditions. For example, Lu et al. used the SUMO simulation platform, which particularly addresses the complexities involved in the mixed traffic flows of human-driven vehicles (HDVs), AVs, and CAVs [33]. By calibrating vehicle behavior parameters such as minimum gap, acceleration/deceleration capabilities, and desired time headway through a Kolmogorov-Smirnov test to understand how these vehicles interact under both sunny and snowy conditions. The study employs three surrogate safety measures: time to collision (TTC), Time-Exposed TTC (TET), and brake rate (BR), to assess real-time crash risk variations. Findings indicate that safety performance significantly improves in both weather conditions when CAVs and AVs are integrated into the traffic flow. Notably, the improvement in avoiding serious conflicts is more pronounced in snowy conditions, suggesting that AVs and CAVs offer substantial safety benefits under adverse weather. Additionally, the study revealed that as MPRs increase, the performance of braking behaviors varies, highlighting the dynamic interaction between vehicle types and penetration rates in traffic systems. Another study evaluated the traffic efficiency and safety of CAVs for a one-lane model in mixed traffic under adverse weather conditions [34]. The research introduces a unified performance index that quantifies overall traffic performance, a novel approach that combines metrics from single and multi-vehicle dynamics. Simulations indicate that increasing the market penetration rate (MPR) of CAVs significantly boosts both traffic efficiency and safety metrics. Notably, CAVs perform better in adverse conditions, suggesting they can substantially enhance traffic flow and safety during inclement weather.

Understanding the behavior of CAVs during adverse weather is crucial for creating a safe and efficient transportation network. While microscopic simulation has been widely utilized to explore the implications of CAVs in real-world scenarios, existing studies predominantly focus on simple traffic configurations, such as single or multi-lane straight roads, and do not adequately represent the complexity of urban or interconnected networks. Furthermore, these studies tend to isolate operational aspects from safety impacts, which limits their applicability in complex transportation planning. Current literature lacks comprehensive analysis combining both operational efficiency and safety of CAVs within complex traffic networks during various weather conditions. This study aims to fill this gap by integrating these elements into a unified framework that evaluates CAVs performance in a more realistic and complex traffic setting. Specifically, the goal of this research is to understand how different adverse weather conditions affect the performance and safety of CAVs, thereby guiding the development of more effective CAV integration strategies. Unlike previous studies, this research utilizes simulation models to assess the impact of CAVs across more complex and realistic network configurations and different weather scenarios. By doing so, it not only addresses the limited scope of network complexity in earlier works but also merges operational and safety evaluations into a single, comprehensive study. This approach allows for a more detailed understanding of the potential and limitations of CAV technologies, highlighting their practical implications for urban transportation planning under varied environmental conditions.

3. Research Methodology

This part delineates the approach utilized to fulfill the main goal of this investigation, which is to assess the impacts of CAVs on traffic flow and safety across different weather scenarios. This study utilizes a simulation model that assumes CAVs operate under ideal conditions without susceptibility to system errors or cyberattacks. This assumption aligns with common practices in initial CAV research, aimed at understanding the upper bounds of technology performance. It is important to note that while this simplifies the analysis, it might not encapsulate all real-world operational challenges. Figure 2 illustrates an overview of the methodology, elaborated upon in the following sections:

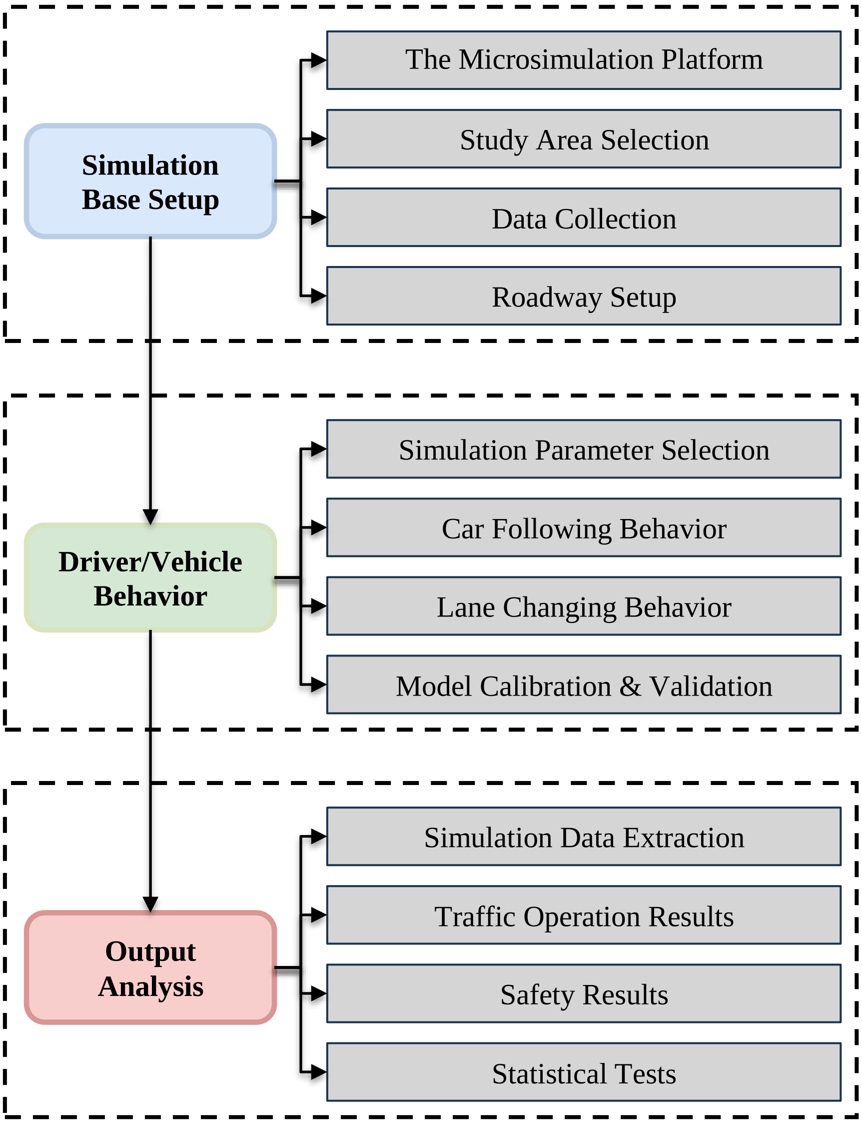


Figure 2. Methodology framework

3.1. The Microsimulation Platform

After an extensive examination of available traffic micro-simulation tools and a thorough assessment of their strengths and weaknesses, PTV - VISSIM emerged as the preferred software for this research. PTV - VISSIM is renowned in the field of traffic micro-simulation, offering the capability to simulate and model diverse traffic elements, such as cars, buses, trucks, trams, bicycles, motorcycles, and pedestrians. Additionally, it can analyze traffic operations under different conditions, encompassing lane setups, traffic compositions, signal systems, and transit stations.

3.1.1. VISSIM's car-following model

A car-following model is used to simulate how one vehicle follows another vehicle by simulating the following vehicle driver's behavior. A vehicle is considered the following vehicle if it is determined by the front or the leading vehicle to adjust and keep a certain speed to avoid a collision. VISSIM uses a psycho-physic model developed by Wiedemann (1974), which is suitable for urban traffic. Its last improvement in (1999) is the Wiedemann 99, which is mainly ideal for interurban (motorway) traffic. The model is called a psychophysical car-following model because it combines psychological aspects and driver perception restrictions. Figure 3 shows the driver perception thresholds and the regimes formed by these thresholds [35].

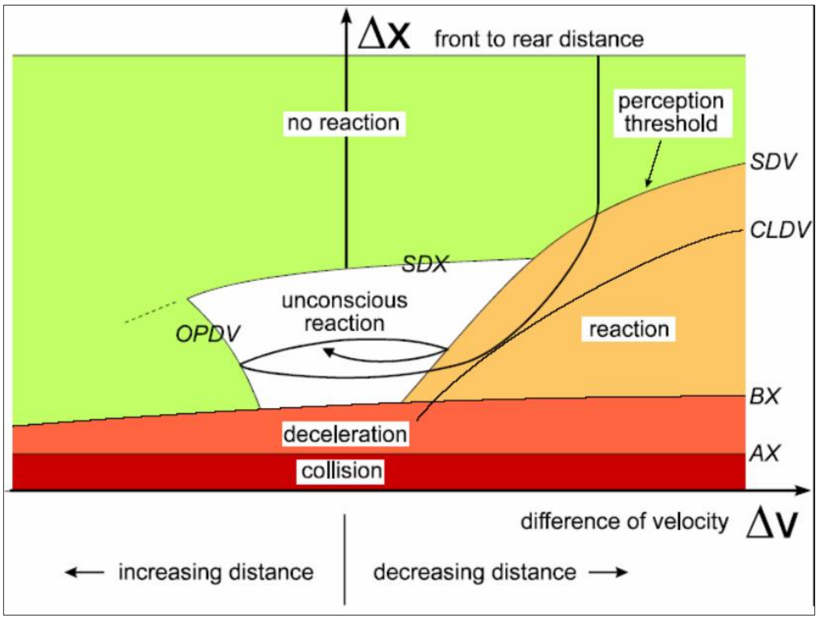


Figure 3. A typical car-following behavior of a vehicle [35]

Where AX is the desired distance between two stationary vehicles, BX is the minimum following distance, which is considered a safe distance by drivers. CLDV are the points at short distances where drivers perceive that their speeds are higher than their lead vehicle speeds; SDV are the points at long distances where drivers perceive speed differences when they are approaching slower vehicles; and OPDV are the points at short distances where drivers perceive that they are traveling at a slower speed than their leader. SDX is the maximum following distance, indicating the upper limit of the car-following process. The basic idea of this model is that the driver can be in one of four regimes. The first is the free driving regime, where no preceding vehicles are observed, allowing the driver to travel freely without their influence. In this regime, the driver aims to reach and maintain his or her desired speed; however, due to imperfect throttle control, the driver's speed will oscillate around the desired speed.

The second is the approaching regime, which occurs when the driver approaches a slower preceding vehicle. Here, the driver will decelerate until the difference in speed is zero to reach the desired safety distance. The third, the deceleration following regime, involves the driver following the preceding vehicle without conscious acceleration or deceleration to maintain the safety distance, but again due to imperfect throttle control, the difference in speed will oscillate around zero. Lastly, the braking regime occurs when the distance falls below the desired safety distance, if the preceding vehicle changes its speed suddenly or a third vehicle changes its lane in front of the vehicle, requiring the driver to apply medium to high deceleration rates to regain the safety distance. Drivers switch between these driving regimes based on certain thresholds that combine speed difference and distance. A vehicle's acceleration is influenced by its speed, speed difference, distance to the preceding vehicle, and the characteristics of an individual driver because each driver has his or her own perception of safety distance, desired speed, and speed difference.

3.2. Base Model Development

The initial step in VISSIM simulation involves network coding. Specifically, the VISSIM base model was established to be utilized in subsequent analyses or scenarios. The construction of speed profiles, coding of vehicle routing, coding of conflict points and priority rules, entering of speed changes, and inputting of vehicle information are among the tasks undertaken.

3.3. Study Area Selection

In the quest for a suitable study site, an aerial image of Sharjah's road network in the UAE was scrutinized. After thorough assessment, a freeway stretches from the junction of E88 and E311 to Wasit Square emerged as the chosen area for this investigation, depicted in Figure 4. The designated segment spans approximately 3 kilometers and comprises eight entry and exit ramps, along with six points for vehicle entry. Utilizing an aerial image, we gauged lane dimensions and lengths for merging, diverging, and connecting areas, shaping the mainline corridor accordingly. This specific section offers an optimal setting for evaluating how connected and autonomous vehicles influence traffic flow and safety across diverse weather conditions.

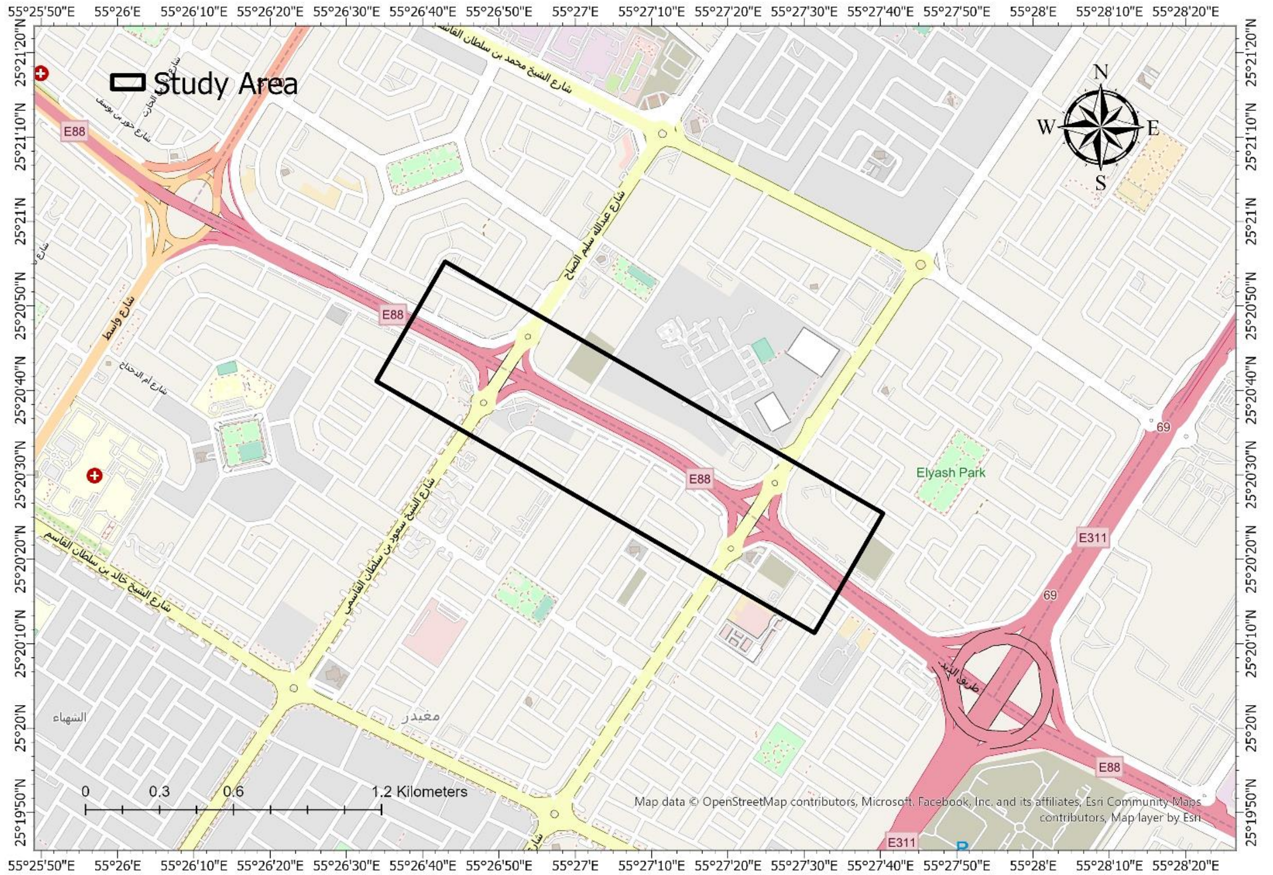


Figure 4. Study area layout (Sharjah, UAE)

3.4. Data Collection

Traffic count data was collected during the morning and afternoon peak periods for a duration of two days within the study area to enhance the accuracy of the microsimulation model. Hourly volumes were obtained by aggregating the counts taken at 15-minute intervals. The highest vehicular volume was observed during the 60-minute intervals from 7:00-8:00 AM and 5:00-6:00 PM, representing the morning and afternoon commuting peaks, respectively. The collected data was utilized to develop a calibration dataset and a validation dataset.

3.5. Simulation Parameters Selection

Since no observational data was available, VISSIM suggested that CAVs could be modeled internally to a certain extent. PTV VISSIM employs two car-following models, specifically Wiedemann 74 and Wiedemann 99, to simulate the driving behaviors of Heavy-Duty Vehicles (HDVs) and Connected Autonomous Vehicles (CAVs) [36]. The model Wiedemann 99 was selected for our study focusing on a freeway segment, following VISSIM's guidance for achieving enhanced accuracy. This model necessitated the calibration and adjustment of numerous parameters to accurately replicate typical CAV driving patterns. These parameters included standstill distance, following distance, longitudinal oscillation, perception thresholds for following, both negative and positive speed differences, the effect of speed on oscillation, oscillation during acceleration, acceleration from a standstill, general acceleration, and the deactivation of stochastic behaviors. The values of these parameters were adjusted on Table 1 based on the findings from previous studies and the CoExist project [10, 37–40]. Although each study seems to have made its own adjustments to the default values, they all have something in common. For example, they will allow the CAV to maintain a closer gap with the front car, respond quicker and more smoothly, observe more vehicles, and consider cooperative lane changing. The different versions of VISSIM can be the reason for some of the discrepancies. Different weather conditions were simulated in VISSIM by adjusting several key parameters that affect driving behavior and vehicle interactions. For each weather condition—Light Rain, Heavy Rain, and Fog—factors such as safe distance, following variability, and sensitivity to speed changes and vehicle headway were modified to reflect the impact of weather on driving conditions. The internal models in VISSIM 21 were altered based on the recommendations from PTV Group and the literature. The simulation lasts 4200 seconds, including a 900-second warm-up period. The analysis is based on data obtained from 900 to 4200 seconds. Furthermore, the vehicle input is made up of 93% passenger cars and 7% heavy trucks based on the distribution obtained from the data.

Table 1. CAV modified driving parameters used in this study benchmarking the literature

Parameter	Default	Hranac et al. [10]	ATKINS [38]	Asadi et al. [39]	He et al. [40]	This study
CC0 (m)	1.5	0.5	0.75	1-1.5	1.25	1
CC1 (sec)	0.9	0.5	0.45	0.5-1.5	0.5	0.5
CC2 (m)	4	0	2	0	3	0
CC3 (sec)	-8	-	-	-8	-12	-8
CC4 (m/s)	-0.35	0	-0.1	0	-0.1	0
CC5 (m/s)	0.35	0	0.1	0	0.1	0
CC6 (rad/s)	11.44	0	0	0	0	0
CC7 (m/s^2)	0.25	0.45	0.25	0.15-0.45	0.25	0.25
CC8 (m/s^2)	3.5	3.9	3.5	3.3-3.9	3.5	3.5
CC9 (m/s^2)	1.5	-	-	1.3-1.9	1.5	1.5
Look-ahead distance	0 to 250 m	-	-	0–800 m	0-500 m	0-500
Look-back distance	0 to 150 m	-	-	0-800 m	0-500 m	0-500
Observed vehicles	2	10	2	10	10	10
Smooth close-up behavior	No	-	-	Yes	yes	yes
Accepted deceleration, trailing vehicle (m/s^2)	-1	-	-	-	-1	-1
Minimum headway, front/rear (m)	0.5	-	-	0.2-0.7	0.37	0.4
Safety distance reduction factor	0.6	-	-	0.3-0.8	0.45	0.5
Maximum deceleration for cooperative braking (m/s^2)	-3	-	-	-	-4	-5
Cooperative lane change	No	-	-	Yes	yes	yes
Maximum speed difference (km/h)	3	-	-	10.8	3	2
Overtake same lane vehicle, minimum lateral distance standing (m) at 0 km/h	1	1	1	1	0.75	0.75
Overtake same lane vehicle, minimum lateral distance driving (m) at 50 km/h	1	1	1	1	0.75	0.75

3.6. Calibration and Validation

The procedure for the model Calibration and Validation is shown in Figure 5.

3.6.1. Model Calibration

In transportation research, some driver behavior metrics significantly impact the performance of mixed traffic but are impossible to measure explicitly in the field. Therefore, adjustments must be made to simulate on-field conditions accurately. To achieve this goal, the microsimulation model must be calibrated to reflect existing or potential field conditions accurately. Before commencing the calibration process, it is essential to establish calibration objectives tailored to the research type and available data. The typical calibration procedure entails identifying the model parameters for calibration, choosing the measures of effectiveness (MOEs) and validation data, defining validation criteria and objectives, and iteratively adjusting the parameters until the model outputs closely align with real-world traffic conditions or fulfill the validation criteria. VISSIM offers a range of parameters that are adjustable during the calibration process.

The impact of VISSIM parameters on model outcomes can be complex and varied. These parameters are organized by their nature, for instance, Driving Behavior Parameters, desired speed, and rates of acceleration and deceleration. For the purpose of calibrating the microsimulation model, traffic volume was selected as the key performance indicator, given its availability in the gathered data set. To adjust the traffic volume figures, the GEH (Geoffrey E. Havers) statistic was applied.

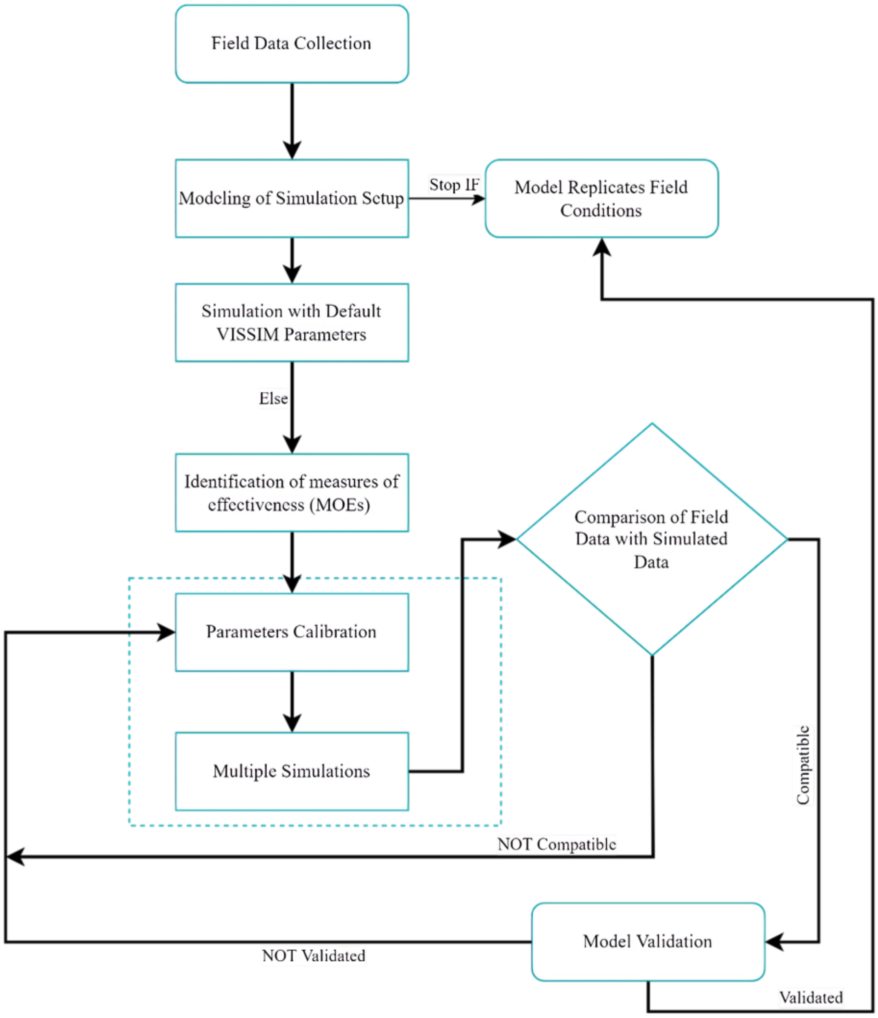


Figure 5. Model Calibration & Validation

Although the GEH formula is not technically a statistical test, it serves as a widely recognized observational tool in the realm of traffic engineering, developed to handle diverse traffic volume datasets and provide a consistent tolerance for volume fluctuations. The calculation of the GEH statistic follows a specific formula:

$$GEH = \sqrt{\frac{2(M-C)^2}{M+C}} \tag{1}$$

In this context, "M" represents the simulated traffic volume (vehicles per hour, vph) produced by the Simulation Model, while "C" denotes the actual observed traffic volume (vph) in the real world. It is essential to calculate the GEH statistic for every mainline link within the simulation. The assessment of how well the simulated traffic volumes match the actual volumes is a critical phase in the model's calibration, with the GEH statistic frequently being the tool of choice for this evaluation. The calibration scope of the microsimulation model encompasses all points of entry and exit, requiring the computation of GEH values for each observed traffic volume. These GEH values act as indicators of the congruence between the modeled and real-world traffic volumes. Specifically, the GEH statistic is categorized into three distinct ranges: GEH<5 indicating a good match, GEH between 5 and 10 signifying a potentially questionable match, and GEH>10 indicating a poor match. Following the Federal Highway Administration (FHWA) guidelines, this study's calibration process adhered to the standards outlined in Table 2 [41], effectively achieving a satisfactory alignment between the simulated and actual traffic volumes.

Table 2. Calibration criteria [41]

Criteria	Target
Within 15%, for 700 vph < flow < 2,700 vph	> 85% of cases
Within 100 vph, for flow < 700 vph	> 85% of cases
Within 400 vph, for flow > 2,700 vph	> 85% of cases
Sum of all link volumes	Within 5% of the sum of all link counts
GEH < 5 for individual link volumes	> 85% of cases
GEH for the sum of all flows	GEH < 4 for the sum of all link counts

The calibration area of the microsimulation model should include all entry and exit points, and the GEH values for each traffic volume should be calculated. The GEH values serve as a measure of the fit between the simulated and observed traffic volumes. Specifically, GEH values are categorized into three ranges: GEH<5 for a good fit, GEH between 5 and 10 indicating a potentially problematic fit, and GEH>10 for a poor fit. Following guidelines from the Federal Highway Administration (FHWA), the calibration results in this study adhered to the criteria outlined in Table 2. The calibration process successfully achieved a satisfactory fit between the simulated and observed traffic volumes.

3.6.2. Model Validation

In the process of model validation, the objective is to ensure that the calibrated model's performance corresponds to actual field measurements that were not employed during the calibration. In addition to the MOEs used during calibration, the validation dataset may comprise data from other model entities (such as travel time corridors) or observations of the same entities under varying traffic conditions or at different times, or even involve the use of different MOEs for the same entities (such as average queue length) [42]. The model is deemed "valid" if the selected MOE or other observations from the unused field dataset is sufficiently close to the simulation value. If this is not the case, driver behavior parameter tuning may be necessary. The study's results indicated that the volume calibration outcomes fulfilled the criterion using the same criteria as presented in Table 2. Additionally, over 90% of freeway or arterial links exhibited a GEH value of less than 5, exceeding the FHWA's acceptance threshold of 85%.

3.7. Penetration Rate

This analysis proposes a set of 21 scenarios, each corresponding to a different weather condition (Clear, Light Rain, Heavy Rain, and Fog), and encompassing various combinations of RV and CAV compositions. To accurately capture the effect of CAVs on traffic dynamics under conditions of low CAV prevalence, the first scenario following the base scenario (which assumes no CAVs) involves a 5% CAV composition, followed by a 5% increment in each successive scenario, until reaching 100% CAV prevalence. Mixed traffic is loaded onto both the mainline and on-ramp in each scenario.

3.8. Number of Simulation Runs

To ensure comprehensive analysis of all possible impacts, a selection of variables will be considered, including 21 penetration rates, four distinct weather conditions, and the implementation of platooning in two different cases. This will result in a total of 168 simulation scenarios. Each scenario will be simulated ten times to account for stochastic variations and obtain stable, statistically significant results, resulting in a total of 1680 runs.

3.9. Traffic Operation Analysis

Given the broad influence of CAVs on traffic dynamics, understanding their effects on traffic operations is crucial. To thoroughly assess their potential impacts and gain a comprehensive understanding of highway networks' future, four key performance indicators were chosen. These encompass average delay, indicating network congestion levels; average speed, reflecting network mobility; travel time, representing total vehicle traversal time; and average number of stops, indicating frequency of vehicle halts.

3.10. Traffic Safety Analysis

In this study, the Surrogate Safety Assessment Model (SSAM) is used to analyze the safety impacts of CAVs. This model, created and validated by the Federal Highway Administration (FHWA) of the United States Department of Transportation, applies various algorithms to detect traffic conflicts from vehicle trajectory data [43]. After each simulation run, VISSIM produces a vehicle trajectory file, which can be obtained through a specific selection in its user interface. This file contains information on every vehicle participating in the simulation. Earlier research conducted by the FHWA has established a conflict-to-crash ratio of approximately 20,000 to 1, based on the relationship identified between crashes and conflicts [43]. Leveraging this research, the equation below is used to estimate the number of accidents [43]:

$$\frac{Crashes}{Year} = 0.119 \times \left(\frac{Conflicts}{Hour}\right)^{1.419} \tag{2}$$

4. Results and Discussion

4.1. Average Speed Results

Figure 6 illustrates the network's average speed across various weather conditions and levels of CAV penetration. Regardless of weather conditions, the data reveals a consistent increase in average speed with higher CAV penetration rates. For instance, in clear weather, speeds range from an initial 24 km/h to a peak of 38 km/h at 100% CAV penetration rate. Conversely, heavy rain shows the lowest initial speed at 17.6 km/h, rising to 32 km/h at full CAV penetration. Notably, heavy rain sees the most substantial speed improvement, with a 100% CAV penetration resulting in an 82% increase compared to clear conditions. Similar improvements are observed in fog (65%), light rain (43%), and clear weather (55%) at full CAV penetration. These findings underscore the significant impact of CAVs on network speed, particularly in adverse weather, attributed to their advanced technologies facilitating real-time information sharing and informed decision-making to mitigate congestion and reduce travel time.

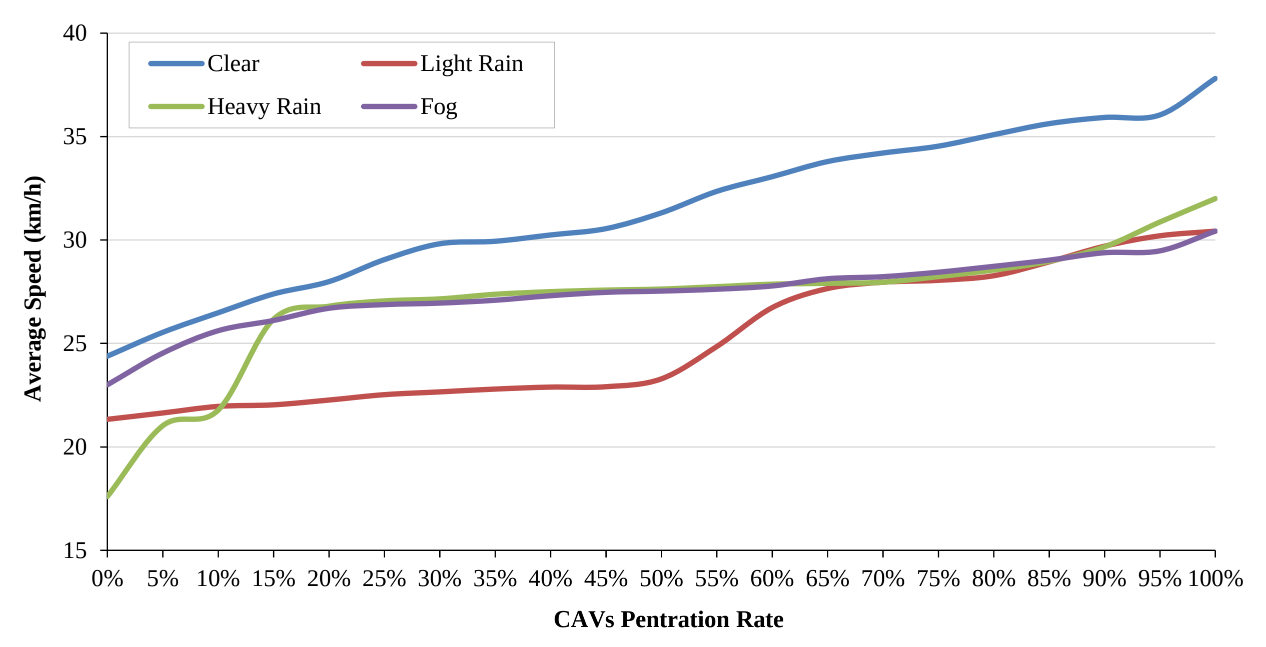


Figure 6. Average speed results of the network under different weather conditions

Table 3 displays the outcomes of an ANOVA analysis conducted on the network's speed outcomes across various weather conditions. This statistical test evaluates whether notable variances exist among the speed outcomes for distinct weather conditions. The findings indicate a noteworthy contrast in the network's speed outcomes across diverse weather conditions.

Table 3. ANOVA test for speed results in the network

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	442.7369	3	147.579	15.3537	5.6E-08	2.718785
Within Groups	768.9559	80	9.611949	-	-	-

4.2. Average Delay Results

Figure 7 illustrates the variations in average wait time and the alteration in this average wait time across various weather scenarios at different levels of connected and autonomous vehicle (CAV) integration. The average wait time, expressed in seconds, serves as a gauge for the congestion level vehicles encounter within the network. The alteration in average wait time reflects the decrease in wait time relative to a baseline scenario with no CAV integration. Analysis of Figure 7 reveals a trend where the average wait time diminishes with an increase in CAV integration, regardless of weather conditions. For example, in clear weather conditions, the average wait time is reduced from 226 seconds with 0% CAV integration to 112 seconds at full (100%) CAV integration. In conditions of heavy rainfall, the average wait time is cut down from 336 seconds at 0% CAV integration to 128 seconds at 100% CAV integration. This decrease in average wait time is particularly notable at higher levels of CAV integration, showing reductions between 25% and 50%. The findings also demonstrate the influence of weather on the network's average wait time, with heavy rain and fog causing the most significant delays at all levels of CAV integration. For example, during heavy rain, delays are approximately 50% longer compared to clear weather conditions at any level of CAV integration. This is due to diminished visibility and the weather's effects on road conditions, hindering vehicles' optimal speed. Furthermore, the data indicates that wait time reductions are more pronounced under poor weather conditions, with heavy rain and fog leading to the greatest decreases in wait time. Specifically, in heavy rain, the adjustment in average wait time ranges from a 27% reduction at 5% CAV integration to a 62% reduction at full integration. This suggests that CAV utilization could markedly mitigate the adverse effects of poor weather on traffic congestion.

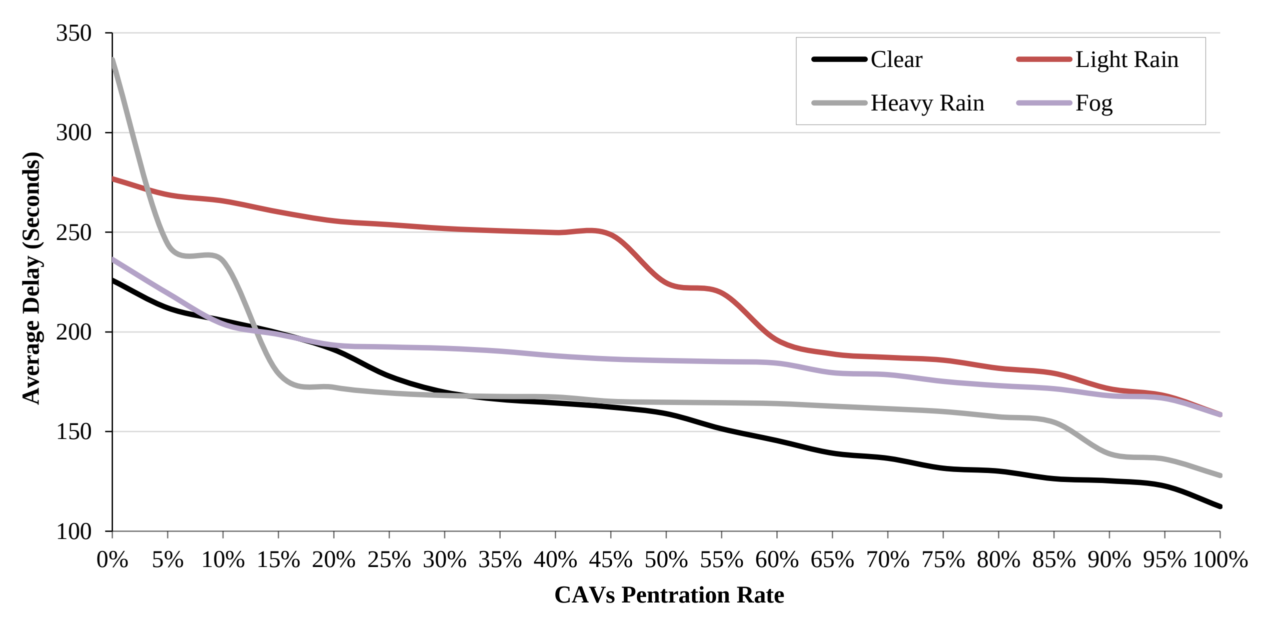


Figure 7. Average Delay results of the network under different weather conditions

Table 4 outlines the outcomes of the ANOVA analysis concerning delay metrics within the network. These findings indicate a statistically significant variation in delay metrics across varying weather conditions.

Table 4. ANOVA test for delay results in the network

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	42436.82	3	14145.61	11.312	2.91E-06	2.718785
Within Groups	100032	80	1250.4	-	-	-

4.3. Average Number of Stops Results

Figure 8 illustrates the variation in the average number of stops across different weather scenarios at varying rates of CAVs penetration. The data reveal a decline in the average number of stops as the penetration rate of CAVs escalates. With no CAVs present, the average stops fluctuated between 226 seconds in clear conditions to 336 seconds during heavy rainfall. Conversely, with full CAV integration (100% penetration rate), the numbers dropped to 112 seconds in clear conditions and to 127 seconds amidst heavy rainfall. The decrease in stop frequency is credited to the enhanced communication and synchronization among CAVs, which diminishes conflicts and halts at intersections. Furthermore, Figure 8 underscores that harsh weather conditions elevate the average stop count.

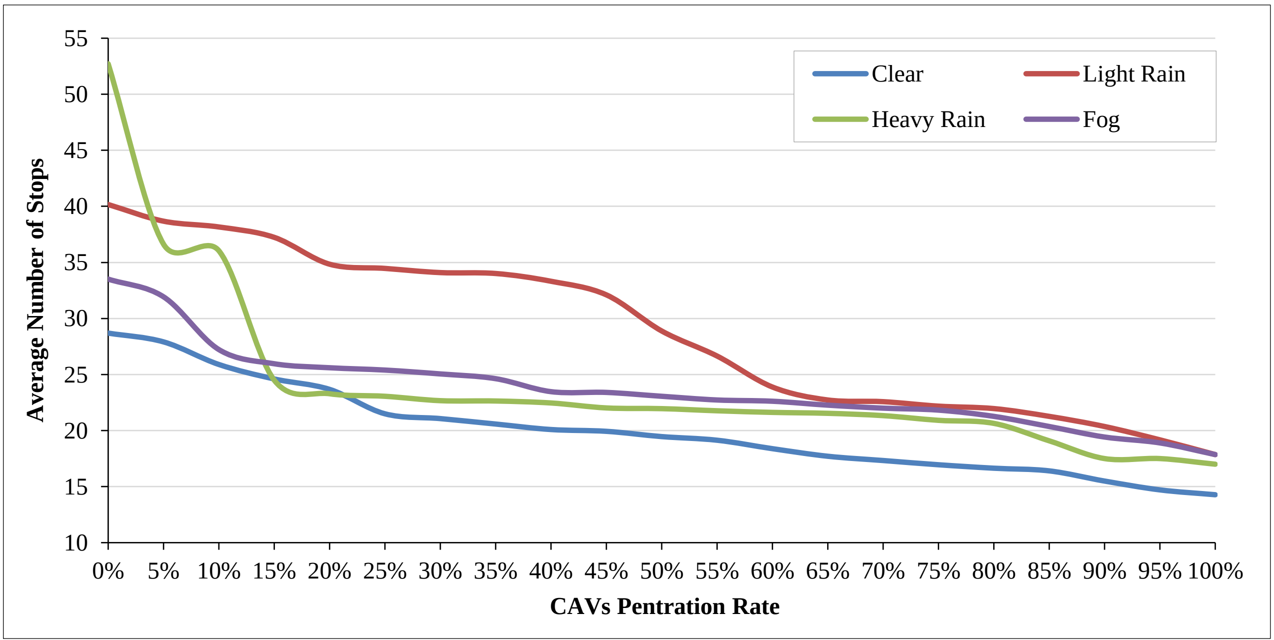


Figure 8. Average number of stops results of the network under different weather conditions

For example, in clear weather, stops varied from 112 seconds to 226 seconds, but under heavy rain, they ranged from 127 seconds to 336 seconds. Adverse weather impacts driving conditions by reducing visibility and altering road surfaces, necessitating slower speeds, longer following gaps, and extended stopping distances. Table 5 presents the findings from the ANOVA analysis aimed at evaluating how varying weather scenarios and levels of CAVs penetration impact the frequency of stops within the network.

Table 5. ANOVA test for the number of stops results in the network

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	813.7723	3	271.2574	7.093893	0.000275	2.718785
Within Groups	3059.053	80	38.23816	-	-	-

The analysis reveals a notable influence of both elements on the stop frequency, as evidenced by an F statistic of F= 7.094 and a P-value = 0.000275. This demonstrates that the weather and the rate of CAVs integration are crucial determinants affecting the network's efficiency regarding stop occurrences.

4.4. Travel Time Results

Figure 9 illustrates a decline in travel time with an increase in CAVs penetration levels. In conditions of clear weather, travel time stands at 1338 hours with no CAV penetration, plummeting to 65 hours (a reduction of 95% at full (100%) CAV penetration. In scenarios of heavy rain, initial travel times of 1436 hours at 0% CAV penetration decrease to 58 hours at full penetration, marking a 96% decline. This data also highlights that adverse weather conditions such as heavy rain and fog significantly extend travel times over those experienced in clear or light rain conditions.

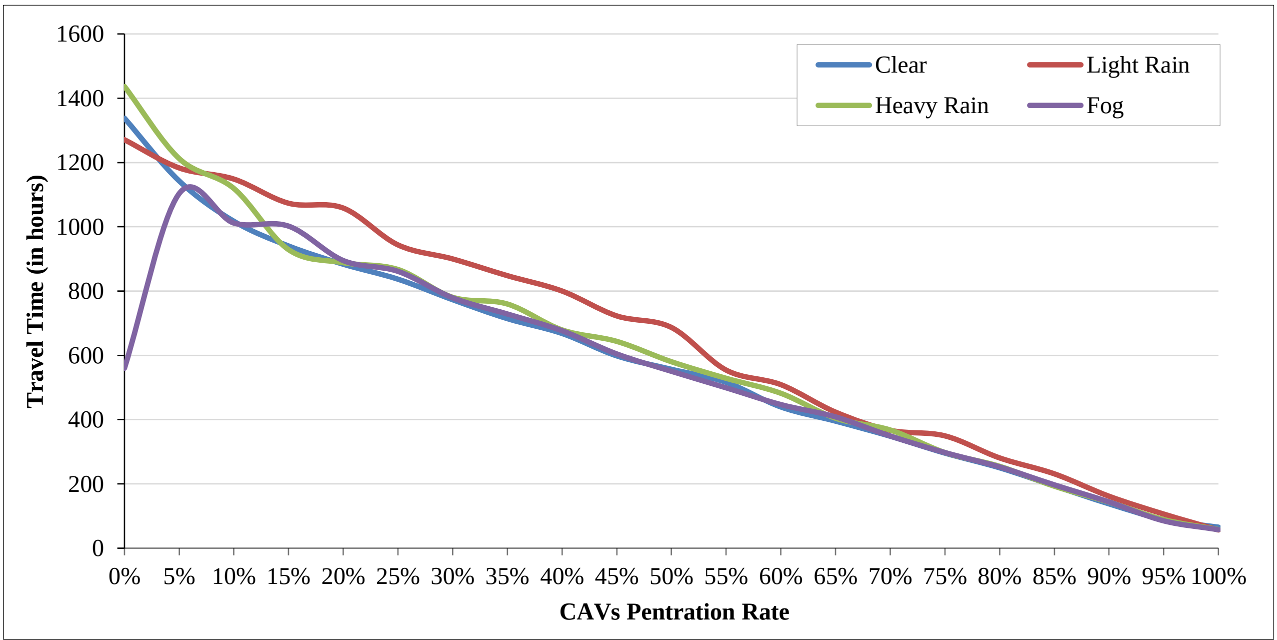


Figure 9. Travel time results of the network under different weather conditions

Table 6 details the outcomes of an ANOVA test conducted on the travel time data within the network, aiming to verify the presence of statistically significant variances in travel times under different weather conditions. With a P-value of 0.823, surpassing the 0.05 threshold for significance, the analysis does not support rejecting the null hypothesis, indicating no notable differences in travel times across the assessed weather conditions.

Table 6. ANOVA test for travel time results in the network

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	118691	3	39563.67	0.302702	0.823352	2.718785
Within Groups	10456144	80	130701.8	-	-	-

4.5. Number of Accidents Results

Figure 10 displays the frequency of accidents within a network across diverse weather scenarios and at different levels of connected and automated vehicles (CAVs) integration. The data demonstrates a clear trend: with a rise in the penetration rate of CAVs, there is a consistent reduction in accident occurrences under every type of weather condition.

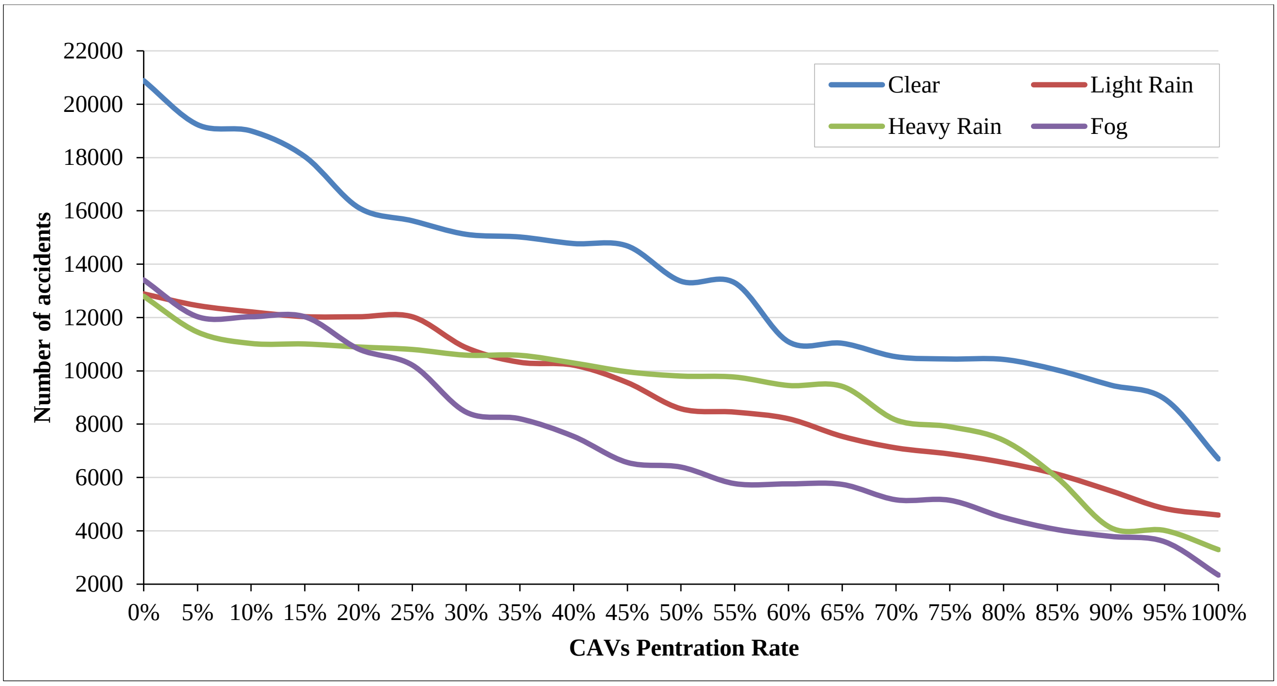


Figure 10. Number of accidents results of the network under different weather conditions

The highest number of accidents occurred in foggy weather conditions, followed by heavy rain, light rain, and clear weather conditions. This is expected as poor weather conditions can impair driver visibility, road surface friction, and vehicle maneuverability, making driving more challenging and increasing the likelihood of accidents. The decrease in the accidents' number is more significant in foggy and heavy rainy weather conditions, indicating that CAVs may be more effective in improving safety under challenging weather conditions. Table 7 outlines the outcomes of the ANOVA analysis regarding accident frequencies within the network, highlighting discernible disparities in accident rates across various weather scenarios and levels of CAVs deployment.

Table 7. ANOVA test for number of accidents results in the network

Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	4.46E+08	3	1.49E+08	15.02465	7.62E-08	2.718785
Within Groups	7.92E+08	80	9904921	-	-	-

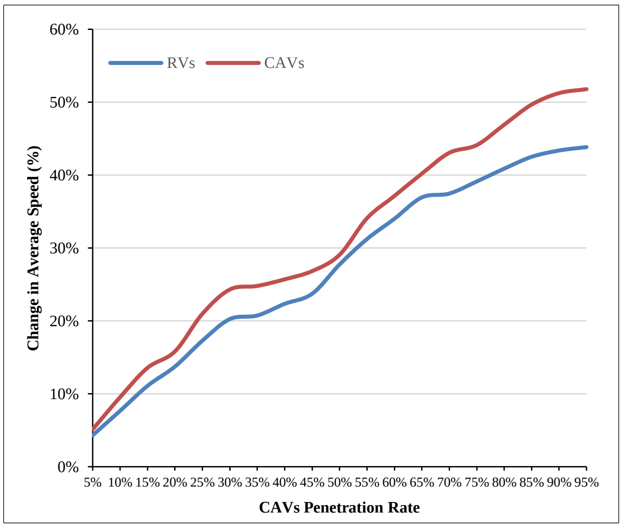
An F-value of 15.02 alongside a p-value of 7.62E-08 underscores that the observed variations in average accident numbers among the groups are statistically significant, implying these discrepancies are unlikely to be the result of random variation.

5. Comparison between RVs and CAVs

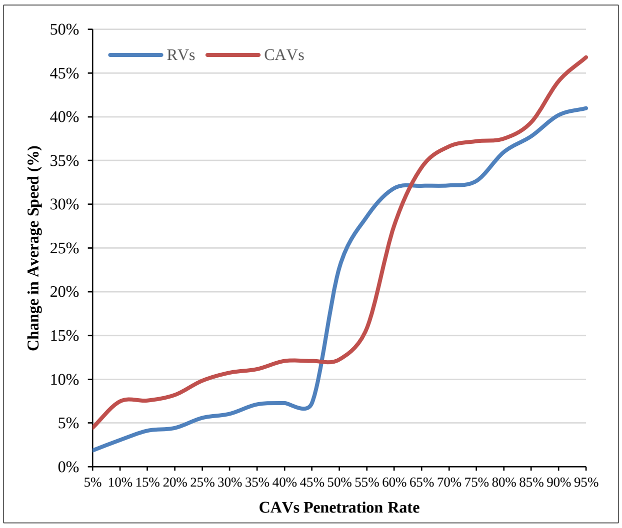
The behavior of various vehicle types was observed to determine any variations in average speed and average delay performance between RVs and CAVs. These findings are addressed in the following sections for each weather condition:

5.1. Average Speed Results

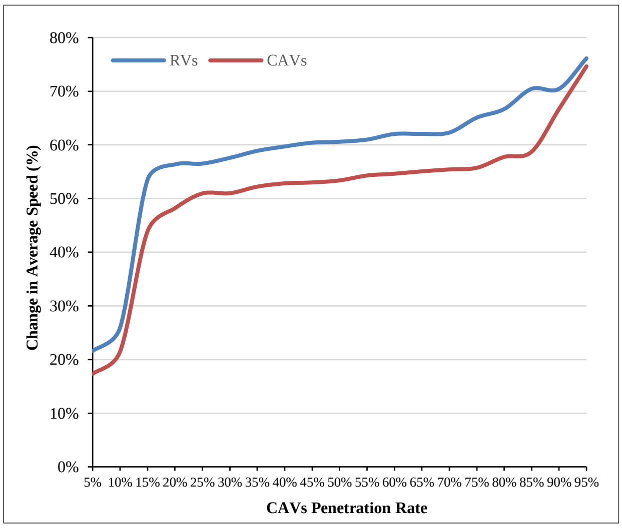
Figure 11 presents the change in average speed under different weather conditions and with different percentages of CAVs penetration rate as compared to RVs. The results show that CAVs can improve traffic flow and reduce travel time, especially in adverse weather conditions. Under clear weather, there is a negligible difference in the average speed of CAVs and RVs, regardless of the CAVs penetration rate. However, in light rain, CAVs' average speed is slightly better than RVs, with an improvement ranging from 1.9% to 4.5% depending on the CAVs penetration rate. In heavy rain, the difference is more significant, with an improvement ranging from 19.4% to 53.5% depending on the CAVs penetration rate. The outcome of this study suggests that CAVs perform better than RVs in wet weather, which could be attributed to the enhanced perception and control capabilities of CAVs in such conditions. In foggy weather, CAVs' average speed is generally better than RVs, with an improvement ranging from 4.3% to 27.9% depending on the CAV penetration rate. Foggy weather poses significant challenges to human drivers due to reduced visibility and the increase in reaction time. CAVs, on the other hand, rely on sensors and cameras that can see through the fog, providing a safer and more efficient driving experience. Moreover, the results indicate that as the penetration rate of CAVs increases, the improvement of the average speed of CAVs over RVs becomes more substantial. For instance, at a 5% CAVs penetration rate, the difference in average speed is minimal. However, at a 95% CAVs penetration rate, the average speed of CAVs is 17.8% to 26.5% better than RVs, depending on the weather condition.



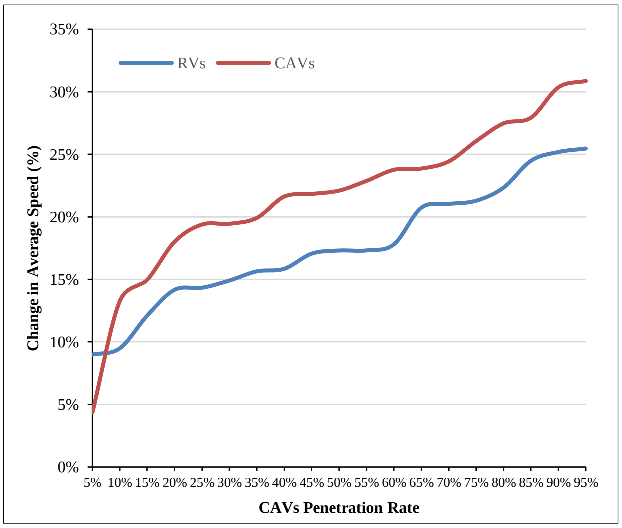
a) Clear



b) Light Rain



c) Heavy Rain



d) Fog

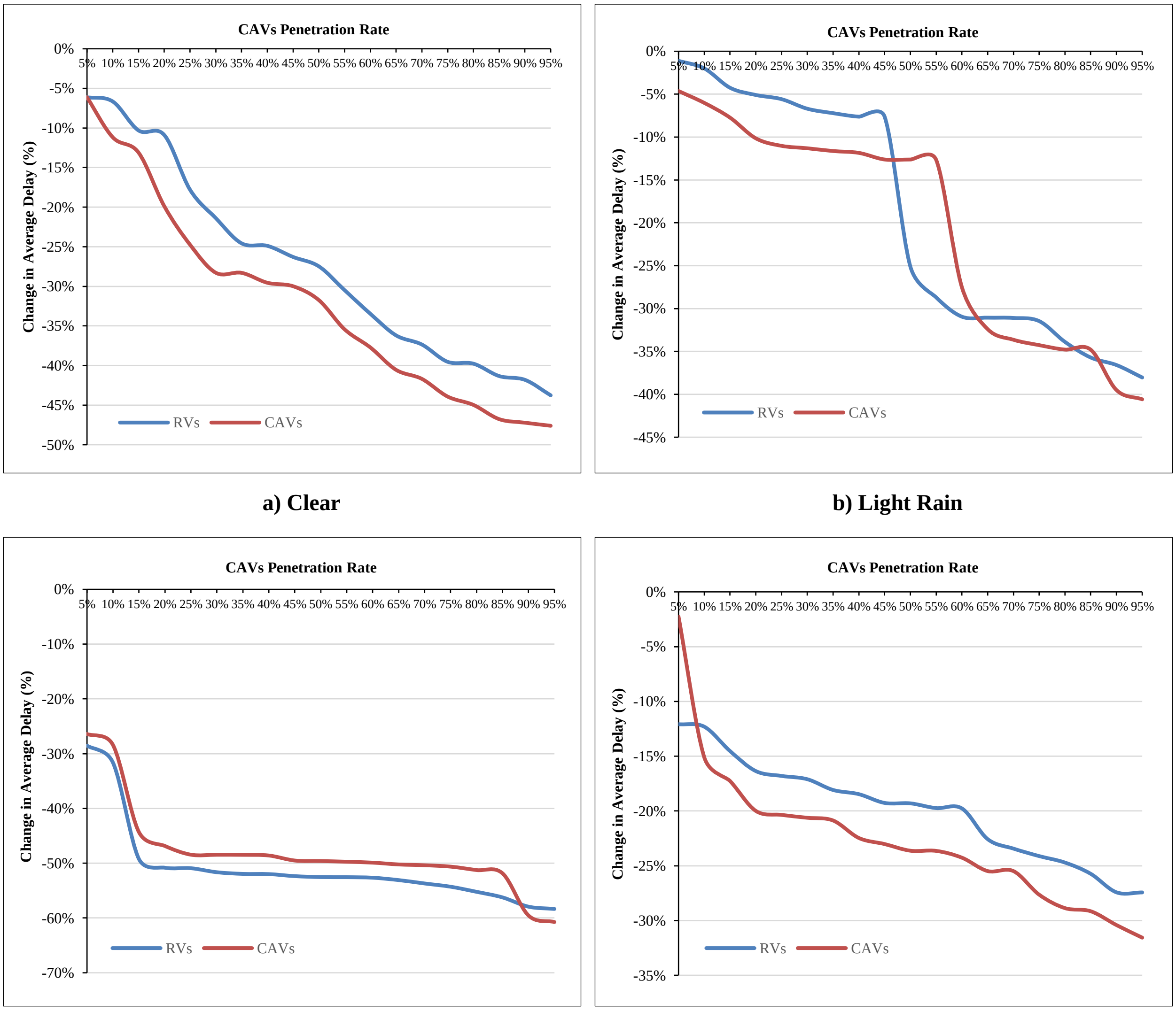
Figure 11. Average speed results for RVs and CAVs under different weather conditions

5.2. Average Delay Results

Figure 12 compares the average delay of RVs and CAVs under different weather scenarios. The average delay is expressed as a percentage of the delay experienced by RVs. The scenarios considered are Clear, Light Rain, Heavy Rain, and Fog, with varying levels of precipitation from 0% to 100%.

The results indicate that CAVs generally experience less delay than RVs under all weather conditions. The difference in delay between CAVs and RVs increases with increasing precipitation levels. Under clear conditions, the average delay for both CAVs and RVs is not available. Under light rain conditions, CAVs experience less delay than RVs, with the average delay for CAVs being 1% to 5% less than RVs. The difference in delay between CAVs and RVs becomes more significant under heavy rain conditions, with CAVs experiencing 26% to 51% less delay than RVs. Similarly, under foggy conditions, CAVs experience 2% to 30% less delay than RVs.

The findings indicate a notable superiority of CAVs (Connected and Automated Vehicles) over RVs (Regular Vehicles) in minimizing delays, particularly during challenging weather scenarios. The disparity in delay times between CAVs and RVs is most pronounced during conditions of heavy rainfall, with fog and light rain following in terms of impact. This evidence suggests that CAVs are significantly more adept at lessening the effects of unfavorable weather on traffic flow.



a) Clear

b) Light Rain

c) Heavy Rain

d) Fog

Figure 12. Average delay results for RVs and CAVs under different weather conditions

6. Summary

The study's findings reveal significant improvements in various performance metrics of traffic networks with increasing integration of CAVs, particularly under diverse weather conditions. The analysis demonstrates that with CAVs, average speeds across the network are notably higher. Specifically, in heavy rain where visibility and road friction are compromised, CAVs' advanced sensing and processing capabilities allow them to adapt and maintain safer and more consistent speeds than human-operated vehicles. This not only reduces travel time but could also lead to a decrease in vehicular emissions due to steadier speeds, illustrating a direct environmental benefit. Furthermore, the reduction in average delays across all weather conditions highlights CAVs' potential to enhance traffic flow efficiency. By leveraging real-time data and advanced algorithms, CAVs appear to optimize routing and reduce idle times. This efficiency in traffic management could result in significant economic savings, with less fuel wasted and more productive time for commuters. The analysis also indicates a decrease in the average number of stops, which is particularly crucial for urban traffic networks where frequent stopping contributes to congestion and increased emissions. CAVs' ability to communicate and synchronize movements may reduce the frequency of stops, likely leading to improved fuel economy and reduced wear on vehicles, which could translate to lower maintenance costs and a reduction in the overall carbon footprint of the transportation sector.

Additionally, by reducing stop frequency, which is often a necessity on slick surfaces during rainy conditions, CAVs contribute to a more constant and safer traffic movement, an element that is crucial for maintaining traction and minimizing collision risks. Travel time reductions are substantially highlighted in the integration of CAVs, with an extended impact during periods of heavy rain and fog. CAVs' continuous adjustments to fluctuating road conditions suggest a heightened reliability in travel time estimations and the potential to shorten the total duration of travel, which is particularly beneficial when adverse weather would otherwise extend it. Lastly, the decrease in the number of accidents with higher CAV integration is perhaps the most compelling outcome, indicating a transformative impact on road safety. The study suggests that the implementation of CAVs could play a crucial role in preventing accidents, particularly in challenging weather conditions such as fog, where human drivers face severe limitations. The integration of CAVs could lead to lower health care costs associated with traffic accidents, lower insurance premiums, and most importantly, save lives. The data presents a compelling case for the advantages of CAVs over RVs, especially under adverse weather conditions. The increased average speeds and reduced delays attributable to CAVs suggest that their sophisticated algorithms are effective in mitigating the impact of weather on driving conditions, thereby enhancing network operation and safety. Essentially, CAVs demonstrate a superior ability to maintain traffic flow and safety in weather conditions that typically impair human driving capabilities. Although direct comparisons to previous studies are limited due to the distinct methodology and outputs of this study as well as the limited literature, the findings verify the existing literature that points to the efficacy of CAVs in enhancing transportation network performance and safety. Consistent with studies like those by Hou et al., which conclude that CAV deployment improves network safety and efficiency [34], this study further supports the role of CAVs in improving traffic management, particularly in challenging weather conditions. This parallel in findings emphasizes the potential of CAVs to significantly mitigate the adverse effects of weather on traffic systems, reinforcing the imperative for continued exploration and integration of CAV technologies.

7. Conclusions

This study represents a pioneering effort to examine, for the first time, the impact of Connected and Autonomous Vehicles (CAVs) on traffic operations and safety under a variety of weather conditions. It utilizes VISSIM for microscopic traffic simulation and the Surrogate Safety Assessment Model (SSAM) for safety evaluations. The study focused on a specifically selected corridor in Sharjah, UAE, analyzing key performance indicators such as average speed, delay, the number of stops, and overall travel time. The outcomes demonstrated that the incorporation of CAVs significantly boosts average speeds and reduces travel times, delays, and stops, notably in challenging weather conditions.

The findings also underscored the ability of CAVs to communicate and coordinate with each other, thus reducing conflicts and stops at intersections, leading to smoother traffic flows. Moreover, the investigation revealed that weather conditions play a significant role in network performance, with conditions like heavy rain and fog causing the greatest increases in delays and stops. Adverse weather was found to lower driving speeds and necessitate greater following and stopping distances, contributing to increased congestion and delays. Nevertheless, the research identified that CAVs have the potential to alleviate the impacts of varying weather on traffic congestion, and to decrease the frequency of stops, delays, and travel times. The insights from this study are invaluable for urban planners and policymakers, offering a glimpse into the advantages of deploying CAVs to enhance traffic efficiency, particularly during adverse weather conditions. The findings and discussions from this research pave the way for further investigations and future research recommendations as follow:

- Explore the effects of various CAV technologies: The current study examined the influence of CAVs on traffic efficiency without delving into the distinct technologies behind CAVs. Future studies could delve into how specific CAV technologies, like platooning and cooperative adaptive cruise control, affect traffic efficiency across a range of weather scenarios and levels of technology adoption.
- This study underscores the importance of future investigations into dynamic traffic demand and complex road geometries to deepen our understanding of CAVs' effects on real-world traffic operations, safety, and efficiency.
- Evaluate the effects of CAVs on emissions and energy use: The present research concentrated on how CAVs influence traffic flow. Future research should explore the effects of CAVs on emissions and energy usage, including their potential environmental advantages, across various weather scenarios and adoption levels to help in developing sustainable urban planning.

In conclusion, it is important to acknowledge key limitations in our study that stem from foundational assumptions made about the behavior of CAVs and the simulation models used to assess their impact. Firstly, assuming that CAVs operate ideally without facing real-world challenges like system errors or cyberattacks might not fully reflect their practical vulnerabilities. Secondly, using modified VISSIM models to simulate CAV behavior, although innovative, lacks empirical validation and could skew results toward favorable outcomes. Future research should focus on integrating real-world data and refining simulation approaches to provide a more accurate assessment of CAV capabilities and limitations. Additionally, the study did not extensively test alternative parameter sets for the VISSIM models used, which is a notable limitation. The parameters were selected based on literature recommendations, but their impact on results through sensitivity analysis was not explored. Future studies should include detailed sensitivity analyses to better determine the dependency of findings on model parameters.

8. Declarations

8.1. Author Contributions

Conceptualization, M.A., A.E., and W.Z.; methodology, M.A. and A.E.; software, A.E.; validation, M.A., A.E., W.Z., and L.W.; formal analysis, A.E. and M.A.; investigation, M.A. and A.E.; resources, A.E. and M.A.; data curation, M.A., A.E., W.Z., and L.W.; writing—original draft preparation, M.A., A.E., W.Z., and L.W.; writing—review and editing, M.A., A.E., W.Z., and L.W.; visualization, M.A. and A.E.; supervision, M.A. and W.Z.; project administration, M.A.; funding acquisition, M.A. and W.Z. All authors have read and agreed to the published version of the manuscript.

8.2. Data Availability Statement

The authors do not have permission to publish the data.

8.3. Funding and Acknowledgements

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8.4. Conflicts of Interest

The authors declare no conflict of interest.

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