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Assessing Low Autonomous Vehicle Penetration Effects on Mobility and Safety at a Rural Signalized Intersection Under Adverse Weather Conditions

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Abstract

Adverse weather conditions significantly degrade mobility and safety at rural signalized intersections, where high approach speeds and limited driver expectancy amplify operational and crash risks. While autonomous vehicles (AVs) have the potential to improve traffic performance, it takes a significant duration to penetrate. During this period, mixed traffic with human drivers and AVs will dominate. In this mixed traffic, the impacts of AVs at low penetration levels on adverse weather remain insufficiently understood, particularly in rural contexts. This study presents a simulation-based assessment of the effects of low AV penetration on mobility and safety at a rural signalized intersection under varying weather conditions. A calibrated microsimulation model was developed using PTV VISSIM to represent clear, rain, and snow scenarios with autonomous vehicles introduced at low penetration rates within conventional traffic. Mobility performance was evaluated using delay, travel time, and average speed, while safety impacts were assessed through surrogate safety measures extracted using the Surrogate Safety Assessment Model (SSAM), including time-to-collision and post-encroachment time. Results indicate that low levels of AV penetration of 10% can improve overall mobility performance compared with conventional traffic, particularly under adverse weather conditions. Safety outcomes show a reduction in conflict frequency and severity under low AV penetration, with more pronounced benefits observed during degraded weather scenarios. Further AV penetration from 10% to 25% may not significantly improve in a rural environment. The findings suggest that early-stage AV deployment may offer measurable mobility and safety benefits at rural signalized intersections, even before widespread adoption. This study provides practical insights for transportation agencies and policymakers regarding the potential role of low-penetration AV integration in enhancing rural traffic operations and safety under adverse weather conditions.

Keywords: autonomous vehicles (AVs); Surrogate Safety Assessment Model (SSAM); time to collision (TTC); Post Encroachment Time (PET); Federal Highway Administration (FHWA); Geoffrey E. Havers (GEH)

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1. Introduction

Intersections are an important component of transportation networks [1], as they connect different traffic movements together and significantly affect both mobility and safety. In rural areas, high-speed signalized intersections pose serious mobility and safety

issues, making it difficult to improve their performance [2]. These challenges are particularly important because national transportation systems rely heavily on rural roads; according to the Federal Highway Administration and United States Census Bureau report, approximately 83% of the total U.S. land area is classified as rural, and around 20% of the total U.S. population lives in these areas [3,4], and they rely heavily on rural roads and intersections for their daily travel. Safety concerns on rural roads are further investigated by the Governors Highway Safety Association. Data from the National Highway Traffic Safety Administration's Fatality Analysis Reporting System show that in 2022, the traffic fatality rate in rural areas was nearly 1.5 times higher than in urban areas, with rates of 1.68 and 1.15, respectively [5]. Various factors affect the severity of intersection crashes, including road geometry design, environmental conditions, driver behavior, and their interactions. Among these, sight distance, road parameters, and bad weather conditions play a crucial role in predicting crash outcomes [6], especially at rural signalized intersections.

Autonomous vehicles (AVs) are one of the emerging technologies that could help future traffic systems improve traffic flow, reduce gas emissions, and make transportation systems safer [7]. Road user safety is important, and AVs can provide numerous safety benefits. One major benefit comes from sensing technology in AVs. Technologies like radar, cameras, and lidar mean that AVs can continuously sense the environment and make driving decisions. This continuous sensing of the environment (360 degrees) provides more extensive and reliable detection than human drivers, which can potentially reduce crashes caused by human error. Furthermore, AVs can respond to changes in traffic conditions more swiftly and more uniformly. This means that AVs can drive safely at higher speeds. AVs not only provide safety advantages but also promote traffic efficiency and environmental performance. Compared with human-driven vehicles, AVs can maintain shorter, more consistent headways between vehicles, improve traffic flow, and reduce unnecessary acceleration and braking [8–10]. However, the connected and autonomous vehicle research ecosystem has focused primarily on highways and urban areas. There has been less research on the unique characteristics of rural roads and signalized intersections, where traffic patterns, driver behavior, and environmental factors differ from those in urban settings [11]. Furthermore, due to the gradual integration of AVs, mixed traffic conditions with low AV penetration rates are likely to prevail for the long term [12]. At such penetration levels, definitive traffic characteristics dominated by AVs are not yet well established, as they remain part of ongoing real-world testing. Under these conditions, a microscopic modeling approach becomes particularly useful, as it allows detailed representation of heterogeneous driving behaviors between AVs and human-driven vehicles [13–16]. Understanding how low AV penetration influences mobility and safety at rural signalized intersections, particularly under adverse weather conditions, therefore remains an important and insufficiently explored research need. To address this gap, the present study evaluates the effects of low AV penetration on traffic mobility and safety at a rural signalized intersection under clear, rain, and snow conditions using a calibrated microsimulation and surrogate safety analysis framework.

2. Literature

2.1. Simulation-Based Studies on Autonomous Vehicles Using PTV VISSIM: Focus and Limitations

Microsimulation modeling of transportation systems has improved a lot over time. It is now safer to use, easier to implement and much more cost-effective than before. Because of this, microsimulation has become a practical tool for evaluating how weather changes affect vehicle behavior and traffic operations, without relying on costly field experiments [17]. Different road environments need different behavior models. Compared

with other microscopic simulation platforms, PTV VISSIM has been used more frequently to study how AVs influence the performance of traffic operations. Researchers have applied VISSIM to intersections, interchanges, and roundabouts, mainly because of its built-in driving behavior models. Recent simulation-based studies suggest that the introduction of AVs can benefit transportation networks in several ways. Congestion tends to decrease, traffic flow becomes smoother, and safety performance often improves. In many cases, road capacity also increases without requiring physical infrastructure expansion. These findings explain why VISSIM has become a preferred tool for evaluating AV impacts under different traffic and road conditions [18,19].

Prior simulation-based studies have primarily focused on AVs in urban traffic environments. The study by Park et al. [20] is one example, where 36 different VISSIM scenarios were developed and the objective was simply to see what Level 4 AVs do to urban traffic flow. The results were encouraging: travel time was reduced, delays dropped, and approach speed increased. As AV penetration increased, the improvements became clearer. At higher AV penetration percentages, travel time decreased by about 17% and delays were reduced by nearly 31%. Average speeds also increased by around 21%.

Aria et al. [21] used the PTV VISSIM internal AV model on an Autobahn segment. Two extreme cases were tested: (1) all vehicles were autonomous; (2) all vehicles were conventional. Driver behavior parameters and speed distributions were adjusted based on studies, especially for car-following and lane-changing behaviors. Again, it shows performance was improved under congestion and traffic density increased by about 8.09% during the evening peak. Average speed also improved by nearly 8.5% and travel time delays dropped.

Taken together, these studies show that AVs can improve traffic flow, reduce delays, and enhance efficiency. However, existing research largely focuses on urban roads, freeways, and high-speed corridors. Rural signalized intersections receive limited attention—and that matters. Higher approach speeds, signal control, and limited driver expectancy create different operating conditions, which become even more complex under adverse weather. Despite this, the topic remains largely unexplored.

2.2. Simulation-Based Safety Assessment Using the Surrogate Safety Assessment Model (SSAM)

Siemens ITS developed the Surrogate Safety Assessment Model (SSAM) with support from the Federal Highway Administration (FHWA). Its purpose is to identify safety issues before actual crashes occur. SSAM relies on vehicle trajectory data generated from microscopic traffic simulation tools, such as VISSIM, PARAMICS, TEXAS, and AIMSUM, to automatically detect and analyze traffic conflicts [22]. The SSAM tool has been used in prior studies to assess traffic safety under various road conditions. Fan et al. [23] estimated traffic conflicts at freeway merge areas by combining both VISSIM and SSAM. The method was simple: real traffic conflicts were manually gathered in the field, and simulated conflicts were taken from the microsimulation model. The two datasets were compared, and the results were encouraging, showing a reasonable level of degree between field-observed and simulated conflicts and defending of SSAM as a surrogate safety evaluation tool, especially in situations where crash data are limited or challenging to obtain. Li et al. [24] investigated how AVs with different levels of automation impact traffic flow and safety by combining VISSIM with SSAM. While SSAM obtained conflict-based safety measures from simulated vehicle trajectories, VISSIM was utilized to represent the driving behavior of various AV types. The findings showed that AV behavior is important to safety results. It has been observed that conservative AV driving patterns have an adverse impact on traffic efficiency and safety since they increase speed variability and, in some situations, lead to more conflicts. Morando et al. [18] used VISSIM and SSAM together to evaluate the

safety consequences of AVs at signalized intersections and roundabouts. They modeled both conventional and autonomous vehicles in their model. After that, surrogate safety metrics, primarily time-to-collision (TTC) and post-encroachment time (PET), were used to examine vehicle trajectories. According to their findings, AVs could reduce possible conflicts in specific situations, which could help resolve the lack of real-world crash data related to AV performance.

2.3. Modeling Driving Behavior and Traffic Flow Under Adverse Weather Conditions

Driving behavior can be greatly impacted by adverse weather conditions like rain, snow, and fog. Although drivers can reduce vehicle speeds and maintain their following distances, these reactions are not always consistent. Reduced visibility might make headway distance and speed selection more difficult, raising operational and safety concerns [25,26]. Many studies have shown the impacts of adverse weather conditions on traffic. Chung et al. studied the impact of rain on driving behavior [27]. According to their investigation, free-flow speeds clearly decreased in wet conditions. The median free-flow speed during dry conditions was roughly 77.7 km/h. This number decreased to roughly 71.4 km/h when rainfall intensity increased to 5–10 mm per hour. These results confirm that even low or moderate rain can significantly influence driver speed selection. Hammit et al. [28] used the SHRP2 NDS dataset to calibrate speed distributions and driving parameters of the Wiedemann 99 (W99) car-following model for different weather conditions. The study first tested the normal clear weather traffic conditions before applying a variety of adverse weather conditions such as rain, fog, and snow. The results of these simulations showed that road capacity did not experience any significant changes during very light and light rain compared with normal weather conditions. However, road capacity did experience changes during moderate and heavy rain. Vehicle speeds increased in fog, very light rain, and light rain, achieving an increase of up to 22%. Speeds were observed to decrease by around 11% in the presence of moderate rain, heavy rain, and snow. These results indicate that driver and traffic behavior when subjected to adverse conditions is non-linear and weather dependent.

Jiaqi Ma et al. [29] investigated traffic behavior in winter weather conditions on Wyoming's I-80. The authors focused on three different scenarios: clear weather, snowy weather, and severe winter weather. The intention was to assist a weather-responsive traffic management system for connected vehicles. To model the weather conditions, the researchers calibrated all 10 parameters of the Wiedemann 99 car-following model (CC0–CC9) in VISSIM. The calibration was mainly focused on capturing changes in driving behavior as road conditions improved after snow. The results showed that driver behavior adjustment—according to weather conditions—was required to realistically simulate traffic in winter conditions.

3. Methodology

3.1. Overall Methodological Framework

This research study establishes a microsimulation-based model to assess mobility and safety performance of conventional and autonomous vehicles at a rural signalized intersection under adverse weather conditions, combining field measurement of traffic and signal data with microsimulation and surrogate safety to assess operational outcomes and safety conflicts in a mixed traffic environment. First, a baseline microsimulation model of the selected rural signalized intersection was created in PTV VISSIM using the field-measured traffic volumes, the observed signal timing plan, and the speed distribution in the approaches. The model was also calibrated to match the current field condition and the observed traffic behavior.

The baseline model was then used to generate a number of simulation scenarios that represented different operating conditions. The simulated operating conditions comprised combinations of weather conditions (clear, rain, and snow) and mixed traffic penetration rates of AVs. Finally, mobility performance measures were obtained directly from the microsimulation model VISSIM, whereas safety performance measures were assessed after post-processing the trajectories generated by VISSIM with the SSAM.

3.2. Study Area Description

The research study site is located in Moab, a small rural community in southeastern Utah. The most recent estimates from the United States Census Bureau indicate that there are approximately 5242 people living in Moab as of July 2024 [30]. Moab, however, serves an important role in regional and through traffic. Moab is classified as a rural community due to its low population density and limited developed infrastructure; the patterns of traffic within this rural region, however, often differ from those in other rural towns. The city of Moab is situated next to several nationally recognized tourist attractions, leading to a significant volume of seasonal and daily traffic. Traffic volume in Moab varies widely throughout the year, with specific increases during the high summer periods of tourism. The study intersection is situated along the US-191 corridor, which functions as the primary north–south arterial through Moab. US-191 experiences a unique mixture of local, transit, and tourist traffic, leading to high traffic volumes despite its rural location. The intersection, which experiences high approach speeds, has signalized controls that necessitate frequent stopping, and experiences unique operational and safety challenges. Moab also has a variety of different weather patterns—like clear skies, rain, and snow—throughout the year. The effects of each of these types of weather conditions have a measurable impact on drivers' behavior—speed choices, vehicle interactions, and much more—providing another justification for why this location was selected for studying the impact of adverse weather on operations and safety. The combination of the rural setting, tourism-based traffic demand, and adverse weather patterns make this roadway and intersection an ideal study location for this project to analyze the impact of AVs on mobility and safety at rural signalized intersections. Figure 1 shows the location of the study area in Moab, Utah, including the city boundary and the US-191 corridor.

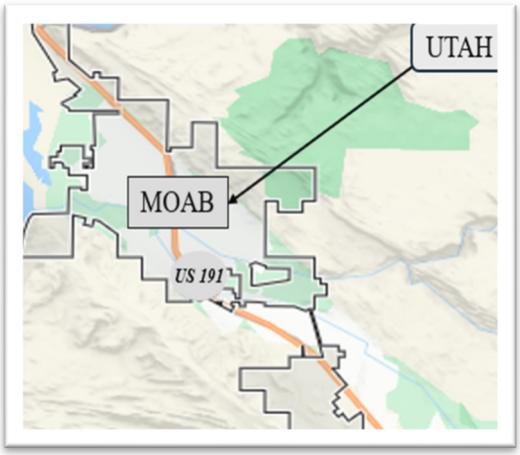


Figure 1. Location of the study area in Moab, Utah, showing the city boundary and the US-191 corridor.

Figure 2 shows the layout of the study intersection along US-191 (N Main Street) in Moab, Utah, including the north–south and east–west approaches.

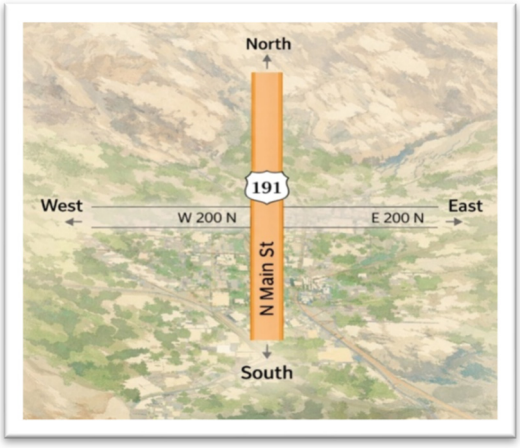


Figure 2. Layout of the study intersection located along US-191 (N Main Street) in Moab, Utah, illustrating the north–south and east–west approaches.

3.3. Data Collection and Microsimulation Model Development

The study's data were first obtained from the Utah Department of Transportation's Automated Traffic Signal Performance Measures (ATSPM) system, which provides high-resolution, detector-based data that can be used to assess many aspects of operational conditions at traffic signal locations. For the rural signalized intersection study in Moab, Utah, turning movement counts, approach speeds, and approach volume data were extracted from the UDOT ATSPM system. Detailed information about the signal controllers at the selected intersection, including the signal timing and phasing plans, was provided by UDOT as an Excel spreadsheet. These field-measured data were then processed to create a representation of the actual demand for and supply of traffic at the intersection and its operation under field conditions. Using the extracted volumes, speed distributions, and signal timing characteristics, an initial (base) microsimulation model of the study intersection was created in PTV VISSIM. This base model was used both to replicate the observed field conditions and to undergo calibration, validation, and additional scenario analyses. Figure 3 shows the development process of the base model in PTV VISSIM, including key steps such as geometry setup, vehicle inputs, signal control configuration, and simulation parameters.

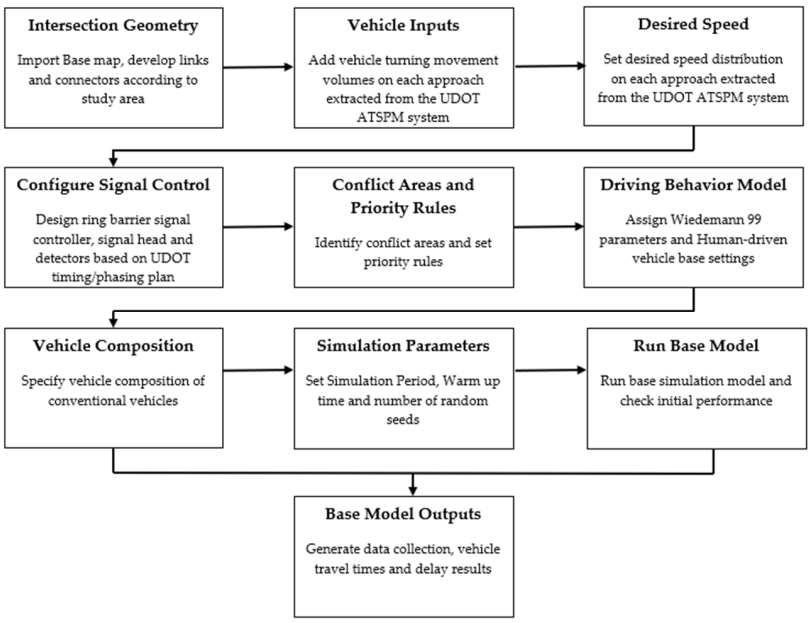


Figure 3. Developing base model in PTV VISSIM.

3.4. Base Model Validation

The base microsimulation model was then calibrated and validated to ensure that the simulated traffic conditions were representative of the observed traffic conditions. The model being representative of field traffic operations at the study intersection was primarily validated through the approach-level speeds and volumes.

3.4.1. Speed-Based Calibration and Validation

Speed calibration and validation confirmed that the microsimulation model accurately produced observed field driving behavior at the study intersection. Approach-level average speeds collected by the UDOT (ATSPM) system served as the main calibration target. The approach speed is an important driving behavior calibration target because it is a critical, sensitive, driving behavior-based input to signalized intersection microsimulation models. Simulated average approach speeds in the PTV VISSIM model were compared to observed ATSPM average speeds using a percentage difference formula:

$$\text{Percent Error } = \left(\frac{|S_{\text{field}} - S_{\text{simulated}}|}{S_{\text{field}}} \right) \times 100 \quad (1)$$

where $S_{\text{simulated}}$ represents the simulated average approach speed obtained from the VISSIM model and S_{field} represents the observed average approach speed obtained from ATSPM data.

Model parameters were adjusted until satisfactory model and observed approach speeds were obtained. In accordance with FHWA-recommended calibration thresholds for microsimulation models, the model was deemed calibrated when the percentage difference in approach speeds was within 10% of observed field conditions for each approach [31]. Simulated northbound, southbound, and westbound speeds were within 10% of observed field speeds for the primary traffic movements (5.7%, 5.7%, and 8.0%, respectively), satisfying the FHWA calibration threshold. The percentage difference in simulated eastbound speeds (44%) was significantly higher than the FHWA threshold; however, this was acceptable given that eastbound was a minor movement at the intersection with only intermittent field observations. In general, calibration of microsimulation models under low-volume conditions can be challenging, and significant variations between simulated and observed parameters are common at rural signalized intersections [31]. The eastbound approach carried only 15 vehicles per hour during the study period, as confirmed by GEH statistics (GEH = 0.53), indicating accurate volume representation. Under such extremely low demand conditions, small variations in arrival patterns and signal delay exposure can produce disproportionately large percentage differences in average speed. Therefore, the observed 44% difference reflects stochastic sensitivity associated with minor-movement operations rather than systematic model miscalibration.

Table 1 presents the model's simulated approach speeds for each movement compared with the observed field speeds. The speed-based calibration validation results suggest that the microsimulation model used in this study is a suitable representation of the observed field traffic conditions for most major movements and that it will provide a solid basis for scenario-based modeling analyses.

Table 1. Comparison of observed and simulated approach speeds for base model validation.

Approach	Field Speed (mph)	Sim Speed (mph)	Percentage Error
Northbound	35	37	5.7%
Southbound	35	33	5.7%
Eastbound	25	14	44%
Westbound	25	27	8%

3.4.2. Volume-Based Validation Using GEH Statistic

Along with validating speeds, traffic volumes were also validated using the commonly used GEH statistic, another commonly used statistic to verify the agreement between simulated and observed volumes. The GEH statistics were calculated in each of the approaches using the ATSPM-based observed approach volumes and the volumes that were simulated by the VISSIM model. The GEH statistics are defined as

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

where M represents the simulated traffic volume and C represents the observed ATSPM traffic volume. Table 2 shows the comparison of observed and simulated approach traffic volumes using GEH statistics.

Table 2. Comparison of observed and simulated approach traffic volumes using the GEH statistics.

Approach	Simulated Average Volume	ATSPM Approach Volume	GEH Value
Northbound	676	681	0.38
Southbound	432	429	0.14
Eastbound	13	15	0.53
Westbound	31	34	0.52

According to standard calibration criteria, a GEH value of less than 5 indicates a good match of simulated and observed volumes [32]. The GEH values for all major approaches were found to be within the acceptable threshold, validating that the base model was able to calibrate the counted traffic demand for the study intersection. The speed- and volume-based validation results presented thus provide confidence that the base microsimulation model accurately reflects existing traffic conditions, allowing for scenario modeling under different weather conditions and AV penetration.

3.5. Simulation Scenarios and Parameter Settings

Following the calibration and validation of the base model, a number of simulation scenarios were developed to evaluate the impact of adverse weather and AV penetration rates on traffic mobility and safety at the above rural signalized intersection. These scenarios were designed to reflect the expected operations of rural signalized intersections under mixed traffic conditions.

3.5.1. Weather-Based Scenarios

Three weather conditions were simulated in this study: clear skies, rain, and snow. The clear-weather condition served as the baseline for all comparisons, while rain and snow were modeled to capture weather-related effects on driver behavior and traffic operations. Weather impacts were incorporated into microsimulation by adjusting key traffic flow parameters, including desired speed distributions and car-following behavior. Reduced approach speeds for rain and snow were selected based on values reported in the literature to reflect more cautious driving under adverse conditions. Driver behavior under rain and snow was modeled using weather-adjusted Wiedemann-99 parameters adapted from Hammit et al. [28], calibrated with SHRP2 Naturalistic Driving Study (NDS) data. These parameters represent increased headway and more conservative vehicle interactions characteristic of adverse weather. Table 3 summarizes the calibrated Wiedemann-99 parameters applied under clear, moderate rain, and snow conditions.

Table 3. Weather-adjusted Wiedemann-99 car-following parameters.

Parameters	Clear	Moderate Rain	Snow
CC0 (m)	4.2	3.8	2.8
CC1 (s)	0.7	0.7	1.2
CC2 (m)	12.7	13.5	11.7
CC3 (s)	−24.6	−24.4	−25.9
CC4 (m/s)	0.0	−0.1	−0.1
CC5 (m/s)	0.9	0.7	0.4
CC6 (rad/s)	1.7	1.5	1.7
CC7 (m/s^2)	1.0	1.4	0.7
CC8 (m/s^2)	1.4	1.0	1.3
CC9 (m/s^2)	0.1	0.1	0.1

3.5.2. Autonomous Vehicle Penetration Scenarios

To accommodate the gradual introduction of AVs to the traffic flow, several levels of AV penetration were tested within these mixed traffic conditions. The non-AV scenarios provided a 0% AV penetration scenario and enabled the observation of the predictable, non-AV traffic conditions. AV penetrations of 10% and 25%, which correspond to the deployment level estimates for these near-future time horizons, were also implemented, with the understanding that the human-driven vehicles will continue to populate the traffic stream at those levels. AVs provided separate behavior settings that recognize their superior sensing capabilities, faster response times, and more consistent car-following behavior relative to human-driven vehicles. PTV VISSIM vehicle composition settings were adjusted to assign the appropriate composition of AVs to the traffic stream, while all remaining vehicles within that stream followed normal, expected behaviors. Table 4 summarizes the key Wiedemann-99 parameters used to distinguish HDV and AV behaviors in the simulation. HDV parameters follow the default Wiedemann-99 settings in PTV VISSIM. AV parameters were implemented based on the modeling approach described by Zeidler et al. (2019) [33], which represents autonomous vehicle behavior within the Wiedemann car-following framework. For AVs, the desired time headway (CC1) was reduced (0.6 s compared to 0.9 s for HDVs) to reflect faster sensing and response, allowing shorter but stable following distances. The standstill distance (CC0) was increased (4.0 m versus 1.5 m) to represent more controlled stopping at queues. In addition, CC3 was adjusted to a more negative value (−40 versus −8) to enable smoother and earlier car-following engagement. Acceleration-related parameters (CC7–CC9) were kept the same for both vehicle types to ensure comparable vehicle dynamics while isolating differences in perception and response behavior.

Table 4. Car-following parameters for HDV and AV.

Modified Parameters	HDV (Default)	AV
CC0 (m)	1.5	4.0
CC1 (s)	0.9	0.6
CC3 (m/s)	−8.0	−40.0
CC7 (m/s^2)	0.25	0.25
CC8 (m/s^2)	3.50	3.50
CC9 (m/s^2)	1.50	1.50

3.5.3. Simulation Execution

For each weather condition and AV penetration scenario, ten simulation runs with different random seeds were conducted to capture the natural variation in traffic operations. The same traffic demand and signal timing settings were used in all scenarios so that

any differences in the results would only reflect changes in weather conditions or AV penetration levels. The results reported in this study represent the average values across these runs, which is a common approach in traffic microsimulation studies to obtain stable results and allow clear comparison of mobility and safety outcomes. In addition, statistical measures including the standard deviation, standard error, and 95% confidence intervals were calculated for the average speed results across the simulation runs to evaluate the variability and reliability of the simulation outputs.

3.6. Surrogate Safety Analysis

FHWA's SSAM was used to evaluate safety in the PTV VISSIM model's vehicle trajectory data. SSAM estimates traffic conflicts using surrogate methods based on the interactions between vehicles. The safety analysis using SSAM considered the standard surrogate safety measures, specifically TTC and PET. In addition, MaxDeltaV was also extracted to account for the severity of conflicts. Furthermore, SSAM separated conflicts into types (i.e., rear-end, crossing, and lane-change conflicts). These surrogate measures and classifications were used to evaluate safety performance and compare the findings between weather conditions and AV penetration rates. The SSAM analysis framework applied in this study is illustrated in Figure 4.

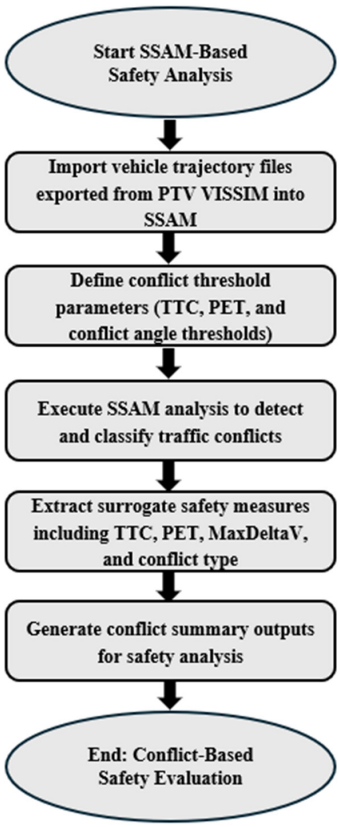


Figure 4. SSAM-based surrogate safety analysis framework.

4. Results and Discussion

This section presents the mobility and safety impacts of AV penetration at the study intersection under clear, rain, and snow weather conditions. Mobility performance was evaluated using approach speed, vehicle delay, and travel time obtained from PTV VISSIM, while safety performance was assessed using conflict-based surrogate safety measures extracted from the FHWA SSAM, including TTC, PET, MaxDeltaV, and total conflicts. Results are compared across 0%, 10%, and 25% AV penetration levels to reflect near-term mixed traffic conditions.

4.1. Mobility Results of Clear Weather Condition

This subsection presents a detailed evaluation of the mobility performance at the study intersection under clear weather conditions. Mobility impacts of increasing AV penetration on the intersection were assessed with the use of average approach speed, average vehicle delay, and average vehicle travel time. Results for 0%, 10%, and 25% AV penetration were compared to determine the impact of low AV penetration on traffic operations with different weather conditions. Average approach speeds can be found in Table 5 for all four approaches.

Table 5. Average approach speeds under clear weather conditions for 0%, 10%, and 25% AV penetration levels.

Approach	Average Speed (mph) 0% AV	Average Speed (mph) 10% AV	Average Speed (mph) 25% AV
Northbound	37.54	38.63	39.83
Southbound	32.89	33.78	34.98
Eastbound	14.17	14.56	15.17
Westbound	27.39	31.66	34.98

Under clear weather conditions, the 0% AV scenario showed average speeds of 37.54 mph in the northbound approach and 32.89 mph in the southbound approach, compared with 14.17 mph in the eastbound approach and 27.39 mph in the westbound approach, reflecting north–south traffic along US-191 and the signal control's impact on the minor eastbound–westbound approaches. After introducing 10% AVs into the model, it showed greater improvements in the average speed of all approaches, with the most notable increase seen in the westbound approach, where speed increased from 27.39 to 31.66 mph, a 16% increase. Northbound and southbound speeds increased to 38.63 mph and 33.78 mph, respectively, while eastbound speed increased marginally to 14.56 mph. Average speeds for all approaches continued to increase with 25% AV penetration, but the marginal improvements relative to the previous scenario were smaller than those at 10% AV levels, indicating diminishing returns of mobility at higher AV penetration levels under signal-controlled operations, where approach speed is still dominated by stopping behavior and signal timing. Northbound and southbound speeds increased to 39.83 mph and 34.98 mph, respectively, while eastbound and westbound speeds increased to 15.17 mph and 34.98 mph, respectively. Figure 5 shows a graphical representation of the average approach speeds of NB, SB, EB, and WB shown in Table 5.

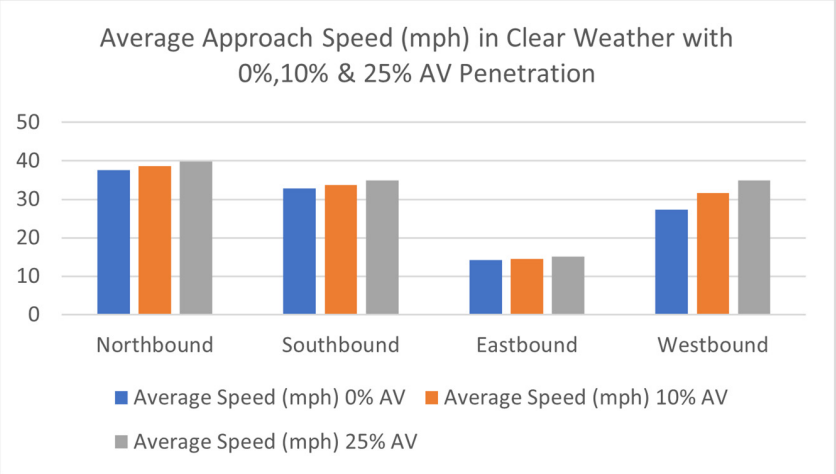


Figure 5. Graphical representation of average approach speeds under clear weather conditions with 0%, 10%, and 25% AV penetration.

To further examine the consistency of the simulation results under clear weather conditions, additional statistical measures were calculated based on the 10 simulation runs. Table 6 presents a statistical summary of clear weather conditions.

Table 6. Statistical summary of average speeds under clear weather conditions.

Direction	Scenario	Mean (mph)	SD	n	SE	t (0.975)	95%CI±	CI Lower	CI Upper
NB	0% AV	37.54	0.94	10	0.30	2.262	0.68	36.86	38.22
	10% AV	38.63	0.89	10	0.28	2.262	0.63	38.0	39.26
	25% AV	39.83	0.75	10	0.24	2.262	0.54	39.29	40.37
SB	0% AV	32.89	1.18	10	0.37	2.262	0.84	32.05	33.73
	10% AV	33.78	0.95	10	0.30	2.262	0.68	33.1	34.46
	25% AV	34.98	0.82	10	0.26	2.262	0.59	34.39	35.57
EB	0% AV	14.17	1.0	10	0.32	2.262	0.72	13.45	14.89
	10% AV	14.56	1.0	10	0.32	2.262	0.72	13.84	15.28
	25% AV	15.17	0.97	10	0.31	2.262	0.70	14.47	15.87
WB	0% AV	27.39	1.43	10	0.45	2.262	1.02	26.37	28.41
	10% AV	31.66	1.32	10	0.42	2.262	0.95	30.71	32.61
	25% AV	34.98	1.82	10	0.58	2.262	1.31	33.67	36.29

Above, Table 6 presents the statistical summary of average speeds under clear weather conditions based on 10 simulation runs. The statistics include the mean, standard deviation, standard error, and 95% confidence intervals. The relatively small standard errors and narrow confidence intervals indicate that the simulation results are consistent across runs, confirming that the reported speed values are statistically reliable and not influenced by random simulation variability. Table 7 shows the average vehicle delay per approach.

Table 7. Average vehicle delay under clear weather conditions for 0%, 10%, and 25% AV penetration levels.

Approach	Average Vehicle Delay (s/veh) 0% AV	Average Vehicle Delay (s/veh) 10% AV	Average Vehicle Delay (s/veh) 25% AV
Northbound	1.7	1.43	1.38
Southbound	1.4	1.33	1.31
Eastbound	39.64	33.27	33.18
Westbound	33.18	39.59	39.59

The baseline scenario (0% AV) had very low average delays of 1.7 s/veh and 1.4 s/veh on the northbound and southbound approaches, respectively, reflecting free-flow conditions in the major north–south corridor (US-191). Much higher delays of 39.64 s/veh and 33.18 s/veh were observed on the eastbound and westbound approaches, respectively, as expected given their lower-priority movements and increased sensitivity to signal controls and approach priority. The average delay across all approaches improved with the introduction of 10% AV penetration, with northbound approaches improving to 1.43 s/veh and southbound approaches improving to 1.33 s/veh. Average delays were most improved on the eastbound approach, which was reduced from 39.64 to 33.27 s/veh (approximately 16% reduction). With the increase in AV penetration to 25%, only marginal improvements were observed on the northbound and southbound approaches, reducing to 1.38 s/veh and 1.31 s/veh, respectively, while the eastbound approach had similar delays as seen in the 10% AV penetration condition (33.18 s/veh), showing that the improvements had almost reached their limits. The westbound approach showed high delays under the 25% AV penetration scenario, at 39.59 s/veh, reflecting increased delays for lower-priority

movements due to signal timing, platooning effects, and stochastic interactions in mixed traffic. Figure 6 shows the graphical representation of the average vehicle delay across AV penetration conditions.

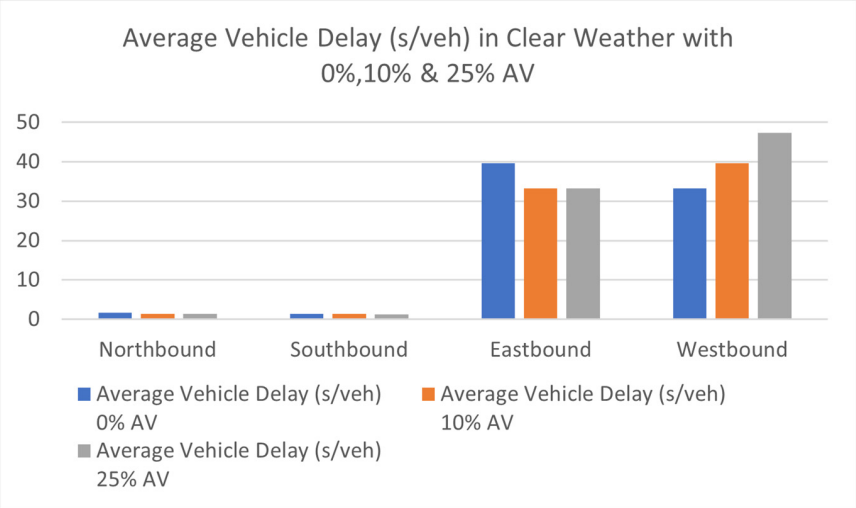


Figure 6. Graphical representation of average vehicle delay under clear weather conditions with 0%, 10%, and 25% AV penetration.

Table 8 presents the average travel times for all four approaches.

Table 8. Average vehicle travel time under clear weather conditions for 0%, 10%, and 25% AV penetration levels.

Approach	Average Travel Time (s) 0% AV	Average Travel Time (s) 10% AV	Average Travel Time (s) 25% AV
Northbound	8.33	8.04	7.98
Southbound	7.96	7.89	7.87
Eastbound	47.46	40.96	40.89
Westbound	40.89	47.41	47.41

The 0% AV scenario showed low average travel times for the northbound and southbound approaches of 8.33 s and 7.96 s, respectively, as expected for the major north–south corridor, while average travel times for the eastbound and westbound approaches were substantially higher at 47.46 s and 40.89 s, reflecting these approaches as minor movements with greater delays caused by signals and lower priority for waiting vehicles. The addition of 10% AVs decreased average travel time for all approaches, with northbound and southbound travel times decreased to 8.04 s and 7.89 s, respectively. The greatest improvement was seen in the eastbound approach, where average travel time decreased from 47.46 s to 40.96 s roughly a 14% decrease in travel time. Another increase in AV penetration from 10% to 25% caused further but minimal reductions in average travel time for the two major approaches, with northbound and southbound travel times dropping slightly to 7.98 s and 7.87 s, respectively. However, eastbound travel time was again the same as in the 10% AV scenario at 40.89 s, indicating the limited average travel time reductions with increasing AV penetration rates for major approaches, while the addition of 25% AVs caused a slight increase in average travel time for the low-priority westbound approach of 47.41 s, indicating the sensitivity of low-priority approaches to changes in signal timing and stochastic interactions with other vehicles within a mixed traffic environment. Figure 7 shows the graphical representation of average travel time of vehicles per AV penetration level.

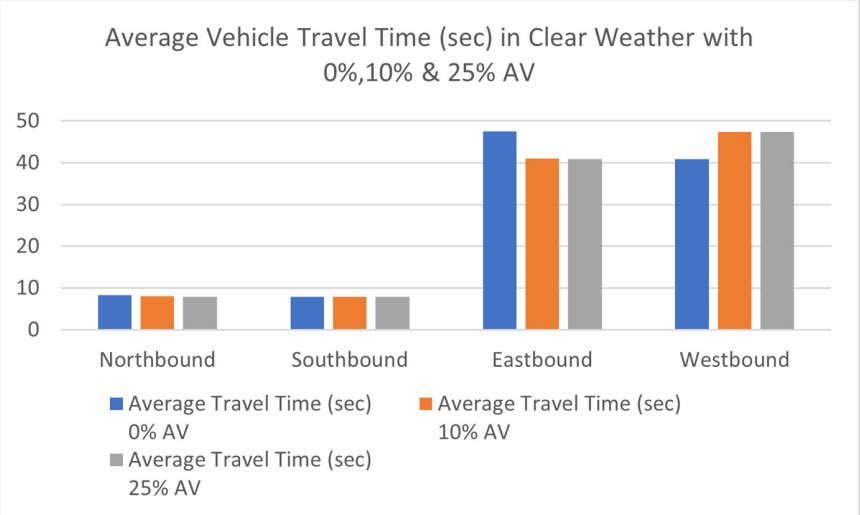


Figure 7. Graphical representation of average vehicle travel time under clear weather conditions with 0%, 10%, and 25% AV penetration.

4.1.1. Rainy Weather Conditions

This section highlights the mobility performance of the study area under rainy weather conditions, assessing average approach speed, average vehicle delay, and average vehicle travel time at 0%, 10%, and 25% AV penetration rates to understand the effect of AVs on mobility performance under adverse weather conditions. Table 9 presents the average approach speed obtained for all four approaches.

Table 9. Average approach speed under rainy weather conditions for 0%, 10%, and 25% AV penetration levels.

Approach	Average Speed (mph) 0% AV	Average Speed (mph) 10% AV	Average Speed (mph) 25% AV
Northbound	34.46	35.99	36.85
Southbound	30.01	31.02	32.31
Eastbound	14.66	5.02	3.27
Westbound	15.70	20.68	22.67

Under rainy weather conditions, the baseline scenario (0% AV) showed lower average approach speeds than in clear weather, at 34.46 mph and 30.01 mph for the northbound and southbound major approaches, respectively, suggesting that drivers are more cautious. Much lower speeds were observed for the eastbound and westbound approaches (14.66 and 15.70 mph, respectively), reflecting the lower priority of these approaches at the intersection and the increased effect of signal control on low-volume approaches, even in adverse weather conditions. The introduction of 10% AVs led to an increase in average speed of the major approaches, with northbound and southbound speeds increasing to 35.99 and 31.02 mph, respectively, while the westbound approach also experienced a major increase in mobility, with speeds increasing from 15.70 to 20.68 mph (an increase of 32%). Interestingly, the eastbound approach recorded a drastic decrease in approach speed to just 5.02 mph, indicating that this low-volume approach is especially sensitive to mixed-traffic interactions and signal timing effects in rain. The 25% increase in AV penetration led to another increase in average speed on the major approaches: northbound and southbound speeds rose to 36.85 and 32.31 mph, respectively, and the westbound approach also benefited, with speed rising to 22.67 mph. The eastbound approach, however, shows another drop to just 3.27 mph, indicating that increased AV penetration rates do not benefit all approaches

equally, even in rain. These very low speeds are primarily influenced by signal delay and extremely low demand rather than unrealistic vehicle behavior. Because the eastbound movement operates intermittently, vehicles often experience full red cycles, causing average speed to become delay-dominated under rainy conditions. Overall, the results indicate that AV penetration benefits mobility for major movements in rain conditions, while mobility impacts for minor movements remain limited by approach priority, traffic demand, and signal control. Average approach speeds by AV penetration level are shown in Figure 8.

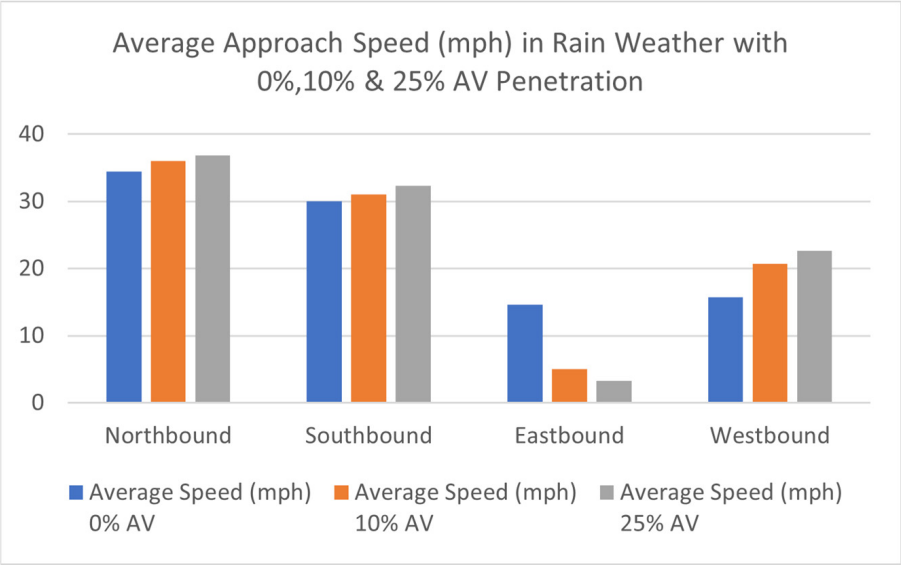


Figure 8. Graphical representation of average approach speed under clear weather conditions with 0%, 10%, and 25% AV penetration.

To further examine the consistency of the simulation results under clear weather conditions, additional statistical measures were calculated based on the 10 simulation runs. Table 10 presents a statistical summary of the results under rainy weather conditions.

Table 10. Statistical summary of average speeds under rainy weather conditions.

Direction	Scenario	Mean (mph)	SD	n	SE	t (0.975)	95%CI±	CI Lower	CI Upper
NB	0% AV	34.46	0.61	10	0.19	2.262	0.44	34.02	34.9
	10% AV	35.99	0.62	10	0.2	2.262	0.45	35.54	36.44
	25% AV	36.85	0.57	10	0.18	2.262	0.41	36.44	37.26
SB	0% AV	30.01	1.01	10	0.32	2.262	0.72	29.29	30.73
	10% AV	31.02	0.91	10	0.29	2.262	0.65	30.37	31.67
	25% AV	32.31	0.68	10	0.22	2.262	0.45	31.86	32.76
EB	0% AV	14.66	0.72	10	0.23	2.262	0.52	14.14	15.18
	10% AV	5.02	1.11	10	0.35	2.262	0.79	4.23	5.81
	25% AV	3.27	1.19	10	0.38	2.262	0.85	2.42	4.12
WB	0% AV	15.7	0.47	10	0.15	2.262	0.34	15.36	16.04
	10% AV	20.68	0.83	10	0.26	2.262	0.59	20.09	21.27
	25% AV	22.67	1.00	10	0.32	2.262	0.72	21.95	23.39

The results above summarize the statistical analysis of average speeds under rainy weather conditions based on 10 simulation runs. The small standard errors and narrow 95% confidence intervals indicate that the simulation results are consistent and statistically reliable. Table 11 presents the average vehicle delay results for all four approaches.

Table 11. Average vehicle delay under rain weather conditions for 0%, 10%, and 25% AV penetration levels.

Approach	Average Vehicle Delay (s/veh) 0% AV	Average Vehicle Delay (s/veh) 10% AV	Average Vehicle Delay (s/veh) 25% AV
Northbound	1.29	1.24	1.18
Southbound	1.26	1.26	1.28
Eastbound	31.35	31.38	31.32
Westbound	37.70	37.77	37.77

In the baseline scenario (0% AV), delays on the northbound and southbound approaches were 1.29 s/veh and 1.26 s/veh, respectively, indicating low average vehicle delay on these major north–south routes despite adverse weather conditions. Considerably higher delays were observed on the eastbound and westbound approaches, 31.35 s/veh and 37.70 s/veh, respectively, reflecting their status as minor movements. The introduction of minor changes occurred with the addition of 10% AVs, with slight decreases in delay occurring on the northbound approach (down to 1.24 s/veh), little change on the southbound approach (still at 1.26 s/veh), and slight increases in delay on the eastbound (31.38 s/veh) and westbound (37.77 s/veh) approaches. An increase to 25% AV penetration resulted in limited effects, varying by approach; delay on the northbound approach decreased slightly again to 1.18 s/veh (approximately a 9% reduction from baseline), while delay on the southbound approach experienced a small increase (1.28 s/veh). A similar decrease was experienced on the eastbound approach (down to 31.32 s/veh), while there was essentially no change on the westbound approach (37.77 s/veh). Overall, these outcomes indicate that during rainy weather conditions, average vehicle delay is low and stable for major approaches for all AV penetration levels, while there is little sensitivity of average vehicle delay for minor approaches to varying percentages of AV penetration, given the strong impact of signal phasing, approach priority, and cautious driver behaviors. Average vehicle delay across all levels of AV penetration is shown in Figure 9.

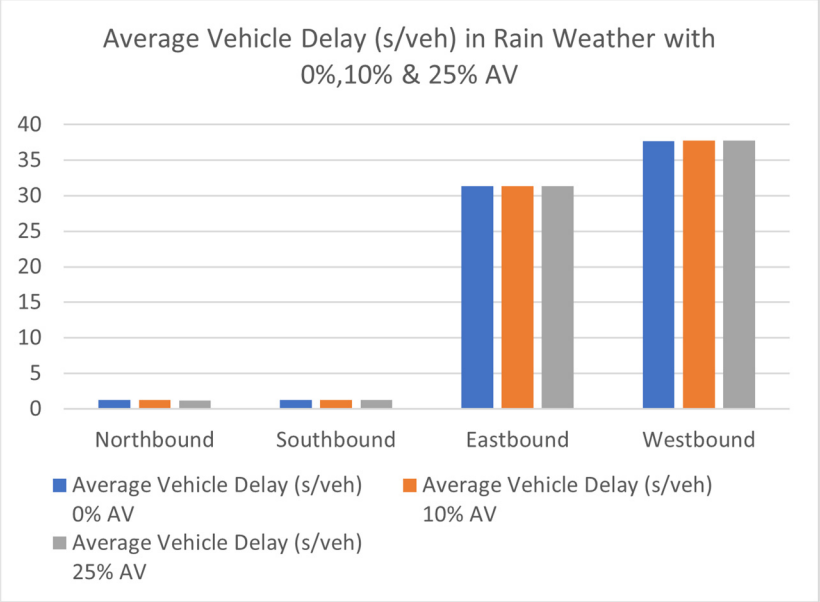


Figure 9. Graphical representation of average vehicle delay under rainy weather conditions with 0%, 10%, and 25% AV penetration.

Table 12 presents the average travel time results for all four approaches.

Table 12. Average vehicle travel time under rainy weather conditions for 0%, 10%, and 25% AV penetration levels.

Approach	Average Travel Time (s) 0% AV	Average Travel Time (s) 10% AV	Average Travel Time (s) 25% AV
Northbound	8.75	8.69	8.64
Southbound	8.71	8.71	8.73
Eastbound	41.64	41.67	41.62
Westbound	48.04	48.10	48.10

The baseline 0% AV scenario observed relatively low average travel times of 8.75 s and 8.71 s on the northbound and southbound approaches, respectively, and free-flowing progression along the major north–south route despite adverse weather conditions. Significantly higher travel times were measured, however, on the eastbound and westbound approaches (41.64 s and 48.04 s, respectively), reflecting the effects of rain on behavior, signal control, and reduced approach priority for minor movements. The introduction of 10% AV penetration resulted in only minor changes in travel time; northbound travel times decreased slightly to 8.69 s, remained unchanged on the southbound approach (8.71 s), and experienced similar negligible increases on the eastbound (41.67 s) and westbound (48.10 s) approaches. The increase in AV penetration to 25% produced similar modest, although approach-specific, effects; northbound travel time again decreased slightly to 8.64 s (an approximately 1.3% reduction from baseline), travel time increased slightly on the southbound approach (8.73 s), and little change was observed on the eastbound (41.62 s) and westbound (48.10 s) approaches. Overall, these findings indicate that under rainy weather conditions, travel time on major approaches remains low with AV penetration; whereas on minor approaches, AV penetration shows minimal difference due to the continued dominance of signal control and cautious driving. Figure 10 provides a graphical representation of the average vehicle travel time trends across AV penetration levels.

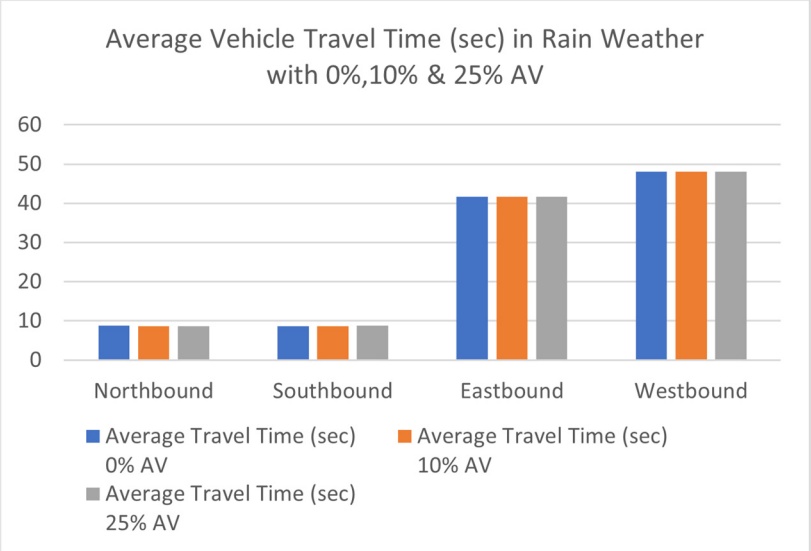


Figure 10. Graphical representation of average vehicle travel time under rainy weather conditions with 0%, 10%, and 25% AV penetration.

4.1.2. Snowy Weather Conditions

This section presents the mobility performance of the study area under snowy conditions, with average approach speeds, average vehicle delay, and average vehicle travel time assessed at 0%, 10%, and 25% AV penetration levels to understand the influence of AVs on

mobility performance under adverse weather conditions. Table 13 presents the average approach speed for all four approaches.

Table 13. Average approach speed under snowy weather conditions for 0%, 10%, and 25% AV penetration levels.

Approach	Average Speed (mph) 0% AV	Average Speed (mph) 10% AV	Average Speed (mph) 25% AV
Northbound	32.11	31.96	32.23
Southbound	28.50	27.70	28.33
Eastbound	13.35	3.14	3.62
Westbound	17.08	20.34	21.67

Under snowy conditions, the baseline scenario (0% AV) experienced significantly reduced average approach speeds for all movements, with average speeds of 32.11 mph for northbound, 28.50 mph for southbound, and substantially reduced speeds for the eastbound and westbound approaches (13.35 mph and 17.08 mph, respectively), as a result of the combined impacts of driver behavior and signal control for minor movements. Adding 10% AV penetration produced mixed results, as evidenced by a slight reduction in average speeds for the northbound (31.96 mph) and southbound approaches (27.70 mph), suggesting that cautious driving behavior still limits mobility to some extent on major approaches following snow, while significant improvement on the westbound approach (17.08 to 20.34 mph) indicates a minor increase in speed as a result of increased AV penetration. The eastbound approach recovered only to 3.62 mph but remained constrained relative to the other approaches. This low speed is primarily associated with signal delay under very low traffic demand, where frequent red-phase exposure reduces the average approach speed rather than indicating unrealistic vehicle behavior. The increase in AV penetration to 25% resulted in speed recovery and relative improvement in mobility for all approaches, with average speeds of 32.23 mph and 28.33 mph for the northbound and southbound approaches, respectively; the westbound approach also improved to an average speed of 21.67 mph (a speed increase of approximately 27% compared with the baseline scenario). The eastbound approach recovered only to 3.62 mph but remains heavily constrained compared with other approaches. Figure 11 shows the graphical representation of the average approach speed for all approaches.

To assess the consistency of the simulation results under snowy weather conditions, additional statistical measures were calculated based on the 10 simulation runs. Table 14 presents the statistical summary of the results.

Table 14. Statistical summary of average speeds under snowy weather conditions.

Direction	Scenario	Mean (mph)	SD	n	SE	t (0.975)	95%CI±	CI Lower	CI Upper
NB	0% AV	32.11	0.59	10	0.19	2.262	0.42	31.69	32.53
	10% AV	31.96	0.59	10	0.19	2.262	0.42	31.54	32.38
	25% AV	32.23	0.55	10	0.17	2.262	0.39	31.84	32.62
SB	0% AV	28.50	0.89	10	0.28	2.262	0.64	27.86	29.14
	10% AV	27.70	0.73	10	0.23	2.262	0.52	27.18	28.22
	25% AV	28.33	0.72	10	0.23	2.262	0.52	27.81	28.85
EB	0% AV	13.35	0.58	10	0.18	2.262	0.41	12.94	13.76
	10% AV	3.14	0.93	10	0.29	2.262	0.66	2.48	3.80
	25% AV	3.62	1.05	10	0.33	2.262	0.75	2.87	4.37
WB	0% AV	17.08	0.44	10	0.14	2.262	0.32	16.76	17.40
	10% AV	20.34	0.58	10	0.18	2.262	0.41	19.93	20.75
	25% AV	21.67	0.70	10	0.22	2.262	0.50	21.17	22.17

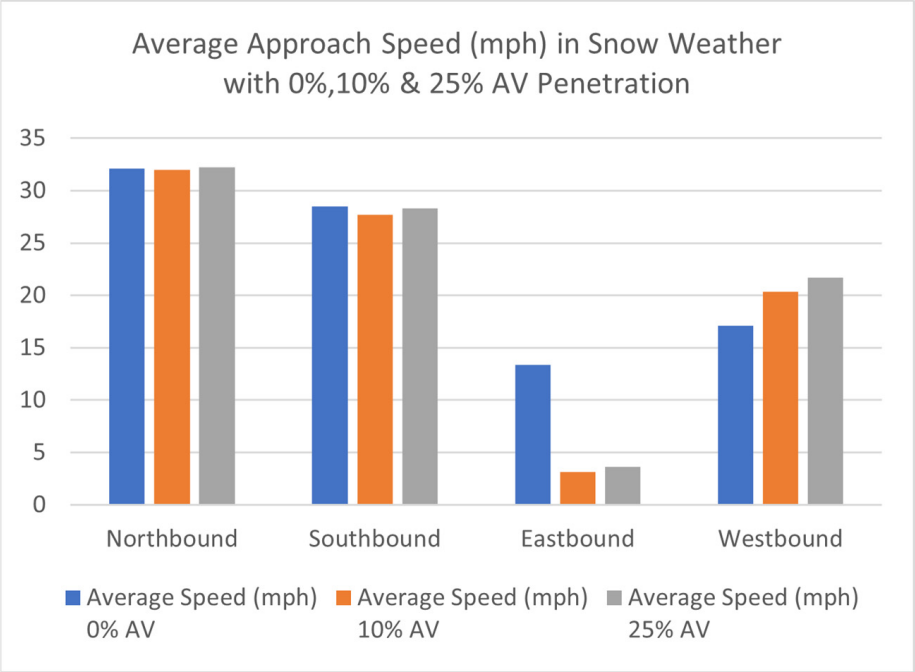


Figure 11. Graphical representation of average approach speed under snowy weather conditions with 0%, 10%, and 25% AV penetration.

The results above summarize the statistical analysis of average speeds under snowy weather conditions based on 10 simulation runs. The small standard errors and narrow 95% confidence intervals indicate that the simulation results are consistent across runs, confirming the statistical reliability of the reported speed values.

Table 15 presents the average vehicle delay results for all approaches.

Table 15. Average vehicle delay under snowy weather conditions for 0%, 10%, and 25% AV penetration levels.

Approach	Average Vehicle Delay (s/veh) 0% AV	Average Vehicle Delay (s/veh) 10% AV	Average Vehicle Delay (s/veh) 25% AV
Northbound	1.22	1.02	1.02
Southbound	1.08	1.10	1.10
Eastbound	31.07	30.63	30.63
Westbound	37.25	37.09	37.09

For the baseline 0% AV scenario, the average vehicle delay on the northbound and southbound approaches was very low (1.22 s/veh and 1.08 s/veh, respectively), indicating that the major north–south traffic movement continued to function well despite the weather conditions. In contrast, major delays were experienced on the eastbound and westbound approaches (31.07 s/veh and 37.25 s/veh, respectively). These delays were caused by reduced speeds and cautious behavior, as well as by the signal control mechanism's effect on minor traffic movements. With a 10% AV penetration, minor reductions in delay were observed for some approaches; northbound delay reduced to 1.02 s/veh, while eastbound and westbound delay experienced a small reduction (30.63 s/veh and 37.09 s/veh, respectively). Southbound delay was almost unchanged (1.10 s/veh). With a 25% AV penetration level, there was no further meaningful reduction in delay; values were like those at the 10% AV penetration level for all approaches—northbound: 1.02 s/veh; southbound: 1.10 s/veh; eastbound: 30.63 s/veh; and westbound: 37.09 s/veh. The model outputs suggest that low AV penetration under snowy conditions results in a small but noticeable reduction in

delays for road users. Figure 12 shows a graphical representation of average vehicle delays per AV penetration level.

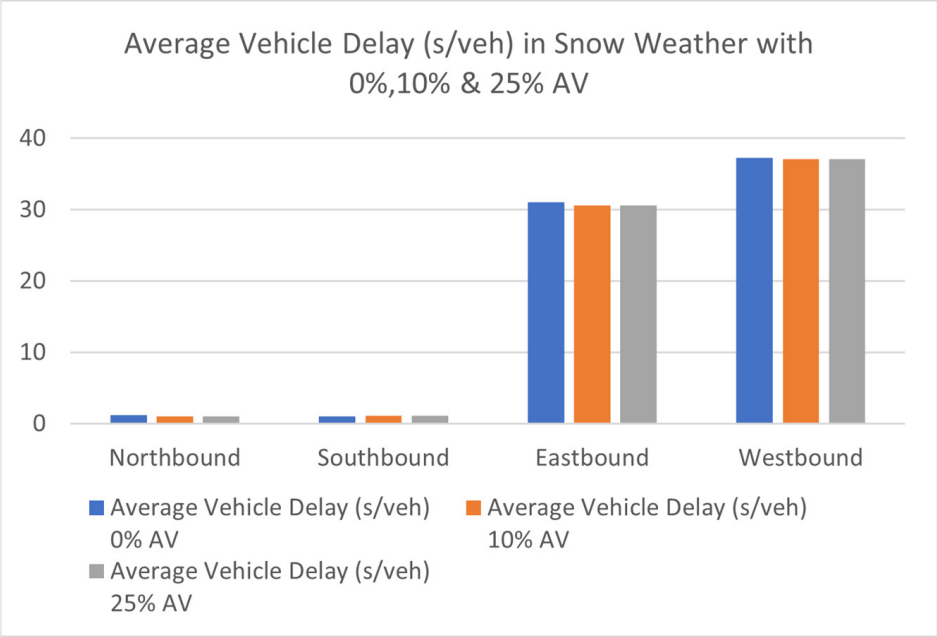


Figure 12. Graphical representation of average vehicle delay under snowy weather conditions with 0%, 10%, and 25% AV penetration.

Table 16 provides the average vehicle travel times for all four scenarios.

Table 16. Average vehicle travel time under snowy weather conditions for 0%, 10%, and 25% AV penetration levels.

Approach	Average Travel Time (s) 0% AV	Average Travel Time (s) 10% AV	Average Travel Time (s) 25% AV
Northbound	9.51	9.87	9.87
Southbound	9.58	9.93	9.93
Eastbound	42.53	42.39	42.39
Westbound	48.78	48.90	48.90

The baseline (0% AV) scenario showing relatively low average travel times on the northbound and southbound approaches (9.51 s and 9.58 s, respectively), indicating consistent operation of those movements. The eastbound and westbound approaches, however, experienced significantly higher average travel times (42.53 s and 48.78 s, respectively), indicating the impact of the reduced speed, more cautious driver behavior, and increased number of stops performed on the snow-impacted road for those minor movements. Adding 10% AVs showed mixed results on average travel time, leading to only slight increases for the northbound and southbound approaches (9.87 s and 9.93 s, respectively), a slight decrease in travel time for the eastbound approach (to 42.39 s), and a slight increase for the westbound approach (to 48.90 s), indicating a lack of sensitivity in the system to detect changes with such low AV percentages in such weather conditions. Adding 25% AVs produced no further meaningful results, as all approach travel times remained identical to those in the previously described 10% AV scenario, suggesting that overall vehicle travel time in these snowy scenarios is more heavily impacted by the adverse weather conditions. Figure 13 shows the graphical representation of average vehicle travel times under snowy weather conditions.

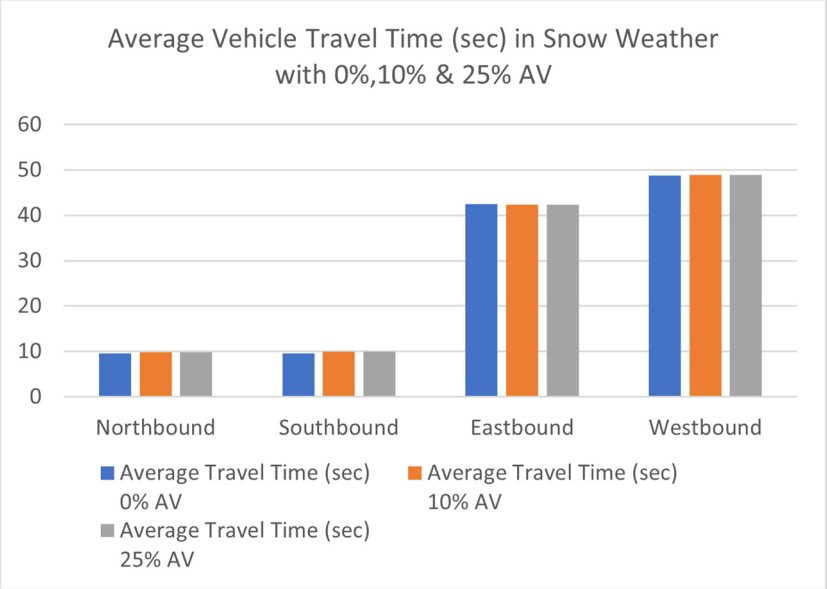


Figure 13. Graphical representation of average vehicle travel time under snowy weather conditions with 0%, 10%, and 25% AV penetration.

To summarize intersection-level performance, approach-level mobility performance measures were summarized into average metrics at the intersection level. For each weather condition and AV penetration scenario, average approach speeds, vehicle delays, and travel times were calculated for the northbound, southbound, eastbound, and westbound approaches to the intersection. These metrics were then averaged at the intersection level across the four approaches using simple (unweighted) arithmetic averaging, which treats each approach equally to enable comparison of mobility performance at the overall intersection level between weather conditions and AV penetration scenarios; whereas approach-level results are described individually in the above subsections.

$$\bar{V}_{int} = \frac{V_{NB} + V_{SB} + V_{EB} + V_{WB}}{4} \quad (3)$$

$$\bar{D}_{int} = \frac{D_{NB} + D_{SB} + D_{EB} + D_{WB}}{4} \quad (4)$$

$$\bar{T}_{int} = \frac{T_{NB} + T_{SB} + T_{EB} + T_{WB}}{4} \quad (5)$$

where

$\bar{V}_{\text{int}}$ = average intersection-level speed (mph);
$\bar{D}_{\text{int}}$ = average intersection-level vehicle delay (s/veh);
$\bar{T}_{\text{int}}$ = average intersection-level travel time (s);
NB, SB, EB, and WB represent northbound, southbound, eastbound, and westbound approaches.

Intersection-level performance measures were calculated using a simple average across the four approaches to enable consistent comparison of operational changes among all movements. Because some approaches at the study intersection carry substantially lower traffic volumes, using a volume-weighted approach could mask operational effects occurring on minor movements. Therefore, an unweighted averaging method was adopted to ensure that operational changes across all approaches are represented in the intersection-level analysis.

Using the aggregation method described above, Table 17 provides average mobility performance measures at the intersection level for various weather scenarios and AV

penetration rates. The table includes summaries of average speed, delay, and travel time, which can help more easily compare mobility results across scenarios.

Table 17. Intersection-level average mobility performance measures across weather conditions and autonomous vehicle penetration levels.

Weather	AV %	Average Speed (mph)	Average Vehicle Delay (s/veh)	Average Travel Time (s)
Clear	0%	27.99	18.98	26.16
Clear	10%	29.65	18.90	26.07
Clear	25%	31.24	18.86	26.03
Rain	0%	23.70	17.90	26.78
Rain	10%	23.17	17.91	26.79
Rain	25%	23.77	17.88	26.77
Snow	0%	22.76	17.65	27.6
Snow	10%	20.78	17.46	27.77
Snow	25%	21.46	17.46	27.77

Under clear weather conditions, intersection-level mobility improved consistently with each increase in AV penetration. Average speed increased from 27.99 mph at 0% AV to 29.65 mph at 10% AV and 31.24 mph at 25% AV. In contrast, average vehicle delay and travel time both experienced only slight, but consistent, reductions (from 18.98 to 18.86 s/veh and from 26.16 to 26.03 s, respectively). These results verify that AVs can achieve their maximum benefits under clear weather conditions, enabling significant improvements in traffic flow and maximizing approach speeds.

Under rainy conditions, AV penetration stabilized intersection-level mobility performance. Average speed fluctuated only slightly with AV penetration levels, but it increased slightly with each increase (from 23.17 mph at 10% AV to 23.77 mph at 25% AV). Average vehicle delay remained low and stable (17.88–17.91 s/veh), and average travel time observed no fluctuations (26.77–26.79 s). These results support the finding that AVs stabilize performance in rainy conditions.

Although snowy weather conditions are the most difficult to operate in, AV penetration still had observable stabilizing effects on intersection performance. Average speed decreased at 10% AV penetration (20.78 mph) but experienced a recovery at 25% AV penetration (increasing to 21.46 mph). Average vehicle delay remained stable across all scenarios (17.46–17.65 s/veh), while average travel time varied only slightly (27.60–27.77 s). This pattern of results supports the conclusion that AV penetration can only partially overcome the disruptions caused by snow by maximizing the likelihood of smooth car-following and higher speeds.

Overall, the intersection-level findings indicate that clear conditions experience the greatest improvements in traffic mobility. However, AV integration also provides useful stabilizing and mobility-maintaining effects under both rain and snow conditions. Even when mobility improvements are relatively minor, AV presence maintains consistent speeds, delays, and travel times during adverse weather, indicating its potential to promote operational resilience for rural, signalized intersections operating under the mixed-traffic conditions likely to be observed soon.

4.2. Surrogate Safety Performance Results

This section evaluates intersection safety using conflict-based surrogate safety measures from the FHWA Surrogate Safety Assessment Model (SSAM). Because crashes cannot be observed in microsimulation and rural intersection crash data are limited, SSAM provides a robust measure for assessing the safety impacts of adverse weather and AV penetration.

4.2.1. Clear Weather Safety Performance

Table 18a summarizes the descriptive statistics of the important surrogate safety measures of TTC, PET, and MaxDeltaV under clear weather and 0% AV penetration as calculated by SSAM. These were all calculated from vehicle trajectory data generated by the PTV VISSIM microsimulation model and used to evaluate conflict severity and crash risk at the study intersection. Table 18b shows the breakdown of traffic conflicts by type.

Table 18. (**a**) Summary of surrogate safety measures at 0% AV penetration under clear weather. (**b**) SSAM-based conflict statistics under clear weather with 0% AV penetration.

(**a**)

Measure	Min	Max	Mean
TTC (s)	0	1.5	0.766
PET (s)	0	4.9	1.253
MaxDeltaV (m/s)	0.013	12.14	4.535

(**b**)

Conflict 194.	No. of Conflicts
Crossing	194
Rear-End	216
Lane Change	125
Total Conflicts	535

The surrogate safety measures suggest critical vehicle conflicts occurred at the study intersection. TTC values between 0 and 1.5 s (mean = 0.766 s) indicate that many high-risk interactions occurred with little time to avoid a collision, especially for rear-end and crossing conflicts at signalized intersections. PET values between 0 and 4.9 s (mean = 1.253 s), compared with the general PET thresholds for critical conflicts, show that PET values below 2 s are generally connected with severe conflicts. This means that many conflicts had limited spatial and time-based clearance between vehicles. MaxDeltaV values ranged from 0.013 to 12.14 m/s (mean = 4.535 m/s), indicating generally moderate conflict severity. Although low TTC and PET values suggest a high safety risk, the average MaxDeltaV indicates that most conflicts were moderate rather than extreme severity.

A total of 535 conflicts were found within the simulated intersection. The most common type was the rear-end conflict (216), which was followed by crossing conflicts (194), and lane-change conflicts (125). The high numbers of rear-end and crossing conflicts align with the expected nature of conflicts at rural signalized intersections, where the influence of signalization, queues, and turning traffic can create various interactions between vehicles. Table 19a shows the summary of surrogate safety measures, while Table 19b presents the breakdown of traffic conflicts by type at 10% AV penetration under clear weather conditions.

The mean TTC was 0.808 s (ranging from 0 to 1.5 s), indicating that, while conflicts remain at low TTC levels, the time to collision between vehicles is slightly improved relative to the baseline scenario with no AVs. In the same way, PET increased as well to a mean of 1.322 s (max 4.9 s), indicating safer interactions at conflict points compared to the baseline scenario. The mean MaxDeltaV was 4.52 m/s (ranging from 0.013 to 12.14 m/s), indicating that conflicts occurred but at a moderate level of severity. The improvement in MaxDeltaV over the baseline scenario suggests that interactions between vehicles were smoother, with less drastic speed differences, in this mixed environment with low AV penetration.

A total of 436 conflicts were generated, with rear-end conflicts (188) being the most common, followed by crossing conflicts (149) and lane-change conflicts (99). The total reduced conflicts compared to the 0% AV scenario indicate that even low AV penetra-

tion provides safety benefits by allowing traffic to become more stable and reducing the incidence of violent vehicle interactions.

Table 19. (**a**) Summary of surrogate safety measures at 10% AV penetration under clear weather. (**b**) SSAM-based conflict statistics under clear weather with 10% AV penetration.

(**a**)			
Measure	**Min**	**Max**	**Mean**
TTC (s)	0	1.5	0.808
PET (s)	0	4.9	1.322
MaxDeltaV (m/s)	0.013	12.14	4.52
(**b**)			
	Conflict Type		**No. of Conflicts**
	Crossing		149
	Rear-End		188
	Lane Change		99
	Total Conflicts		436

Table 20a shows the summary of surrogate safety measures, while Table 20b presents the breakdown of traffic conflicts by type at 25% AV penetration under clear weather conditions.

Table 20. (**a**) Summary of surrogate safety measures at 25% AV penetration under clear weather. (**b**) SSAM-based conflict statistics under clear weather with 25% AV penetration.

(**a**)			
Measure	**Min**	**Max**	**Mean**
TTC (s)	0	1.5	0.785
PET (s)	0	4.6	1.336
MaxDeltaV (m/s)	0.013	12.14	4.468
(**b**)			
	Conflict Type		**No. of Conflicts**
	Crossing		119
	Rear-End		162
	Lane Change		87
	Total Conflicts		368

At 25% AV penetration, the mean TTC was 0.785 s (max. 0 to 1.5 s), lower than in the 10% AV scenario. Similarly, mean PET was higher at 1.336 s (max. 0 to 4.6 s), representing the highest average PET of any AV penetration scenario. It is encouraging that higher PET values align with crossings and turning conflicts, suggesting that high AV penetration correlates with more conservative gap acceptance and better spatial separation at conflict points. Finally, the mean MaxDeltaV was lower at 4.468 m/s, although the maximum values remained comparatively high, ranging from 0.013 to 12.14 m/s. These lower averages, compared with both the baseline and the 10% AV, indicate a further reduction in conflict severity.

The 25% AV penetration scenario resulted in 368 conflicts. The rear-end (162) remained the predominant conflict type, followed by crossing (119) and lane-change (87). The total number of conflicts is a significant reduction from the 0% and 10% AV scenarios, indicating that higher AV penetration is beneficial for overall intersection safety performance. Figure 14 provides a graphical representation of the comparison of the number of traffic conflicts by conflict type (crossing, rear-end, and lane-change) under clear weather conditions with 0%, 10%, and 25% AV penetration levels.

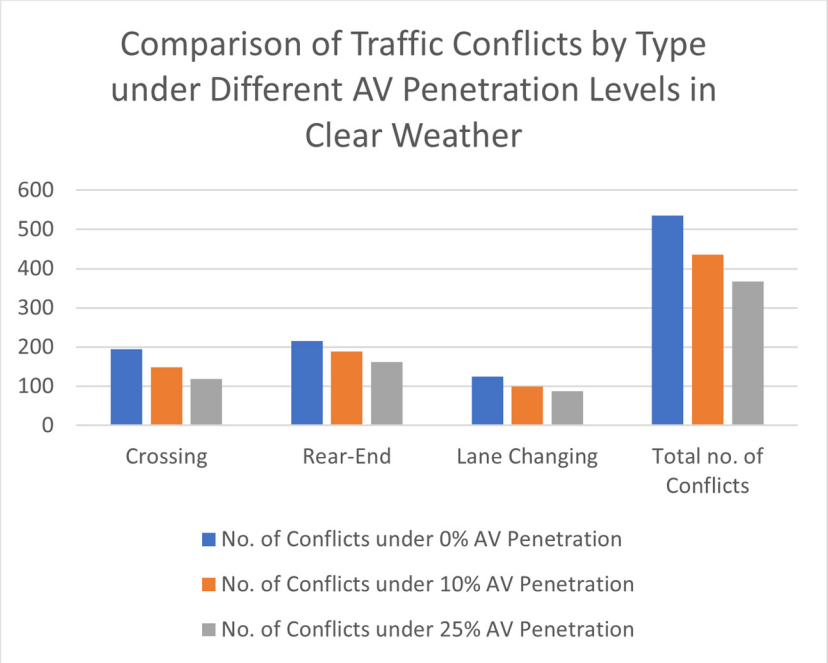


Figure 14. Graphical representation of the comparison of traffic conflicts under clear weather conditions with 0%, 10%, and 25% AV penetration.

4.2.2. Rainy Weather Safety Performance

Surrogate safety outcomes under rainy conditions with 0% AV penetration indicate limited interactions and increased conflict potential. Table 21a shows TTC, PET, and MaxDeltaV outputs while Table 21b shows the breakdown of traffic conflicts by type.

Table 21. (**a**) Summary of surrogate safety measures at 0% AV penetration under rainy weather. (**b**) SSAM-based conflict statistics under rainy weather with 0% AV penetration.

(**a**)			
Measure	**Min**	**Max**	**Mean**
TTC (s)	0	1.5	0.801
PET (s)	0	4.6	1.29
MaxDeltaV (m/s)	0.03	10.23	3.884

(**b**)	
Conflict Type	**No. of Conflicts**
Crossing	160
Rear-End	239
Lane Change	129
Total Conflicts	528

In rainy conditions with 0% AV penetration, the mean TTC was 0.801 s (min = 0 s, max = 1.5 s), representing a close-following distance and a small margin for driver reaction time. The low mean and maximum TTCs in wet conditions highlight visibility issues that impact drivers' behavior. The mean PET was 1.29 s (max = 4.6 s), indicating relatively low mean and maximum PET values (2 s or less), and the potential for severe rear-end and crossing conflicts is high, as PET values at or below 2 s are commonly associated with increased conflict severity. The mean MaxDeltaV was 3.884 m/s (min = 0.03 m/s, max = 10.23 m/s), representing relatively moderate values, indicating that conflicts still occurred.

A total of 528 conflicts were observed. Rear-end conflicts were the most significant (239), followed by crossing conflicts (160) and lane-change conflicts (129). The high number

of rear-end collisions indicates that drivers experience visibility issues on wet pavement, confirming earlier conclusions about adverse weather conditions at signalized intersections. Overall, the rainy weather baseline scenario indicates that adverse surface and visibility conditions lead to significant reductions in traffic safety, resulting in frequent and severe vehicle interactions under typical operating conditions. These findings will serve as a baseline for assessing the impact on safety resulting from the introduction of AVs under rainy conditions in the following scenarios. Table 22a summarizes the surrogate safety measures at 10% AV penetration while Table 22b shows the breakdown of traffic conflicts by type.

Table 22. (**a**) Summary of surrogate safety measures at 10% AV penetration under rainy weather. (**b**) SSAM-based conflict statistics under rainy weather with 10% AV penetration.

(**a**)

Measure	Min	Max	Mean
TTC (s)	0	1.5	0.846
PET (s)	0	4.6	1.442
MaxDeltaV (m/s)	0.133	9.89	3.577

(**b**)

Conflict Type	No. of Conflicts
Crossing	67
Rear-End	127
Lane Change	61
Total Conflicts	255

Under rainy conditions with 10% AV penetration, the mean (TTC) was 0.846 s (range: 0 to 1.5 s), indicating that longitudinal gaps in the traffic stream were greater, and fewer extreme critical interactions occurred compared with the baseline scenario. This increase is due to the smoothing effect of AV car-following behavior during rainy conditions. The mean (PET) also increased to 1.442 s (maximum: 4.6 s), suggesting greater spatial gap acceptance at conflict points and more cautious gap acceptance during crossing and turning activities. The mean MaxDeltaV decreased to 3.577 m/s (range: 0.133–9.89 m/s), signaling reduced conflict intensity and severity of potential collisions. Overall, these findings indicate that even low levels of AV penetration under rainy conditions help achieve safer vehicular conflicts by enabling more cautious acceleration–deceleration and conflict avoidance.

The total number of conflicts dropped significantly to 255 compared with the 0% AV rain scenario. The most prominent conflict type remained rear-end (127 conflicts), followed by crossing (67) and lane-change (61). This reduction in total conflicts shows that even low AV penetration improves safety in adverse weather. Table 23a summarizes the surrogate safety measures at 25% AV penetration while Table 23b shows the breakdown of traffic conflicts by type.

The mean (TTC) under rain at a 25% AV penetration was 0.797 s (range: 0–1.5 s), which was lower than in the 10% AV scenario, indicating that this typical interaction still exists but some close-following interactions are present under mixed traffic and signalized conditions. The mean (PET) was 1.31 s, with a maximum of 4.6 s, which is also lower than the 10% AV scenario but still higher than the baseline scenario. The mean MaxDeltaV was 3.854 m/s (range: 0.266–9.89 m/s), similar to the 10% AV scenario and lower than that of the baseline rain scenario, indicating continued reductions in conflict severity.

Under the 25% AV scenario, the total number of conflicts was 297, higher than in the 10% AV scenario but still lower than in the baseline 0% AV scenario. The typical conflict types were again rear-end (132 conflicts), followed by crossing (92 conflicts) and

lane-change (73 conflicts). This finding suggests that although AV penetration improves safety performance, conflicts can still arise from interactions between AVs and non-AVs. Figure 15 presents a comparison of the number of traffic conflicts by conflict type (crossing, rear-end, and lane-change) in rainy conditions for 0%, 10%, and 25% AV penetration rates.

Table 23. (**a**) Summary of surrogate safety measures at 25% AV penetration under rainy weather. (**b**) SSAM-based conflict statistics under rainy weather with 25% AV penetration.

(**a**)			
Measure	**Min**	**Max**	**Mean**
TTC (s)	0	1.5	0.797
PET (s)	0	4.6	1.31
MaxDeltaV (m/s)	0.266	9.89	3.854

(**b**)	
Conflict Type	**No. of Conflicts**
Crossing	92
Rear-End	132
Lane Change	73
Total Conflicts	297

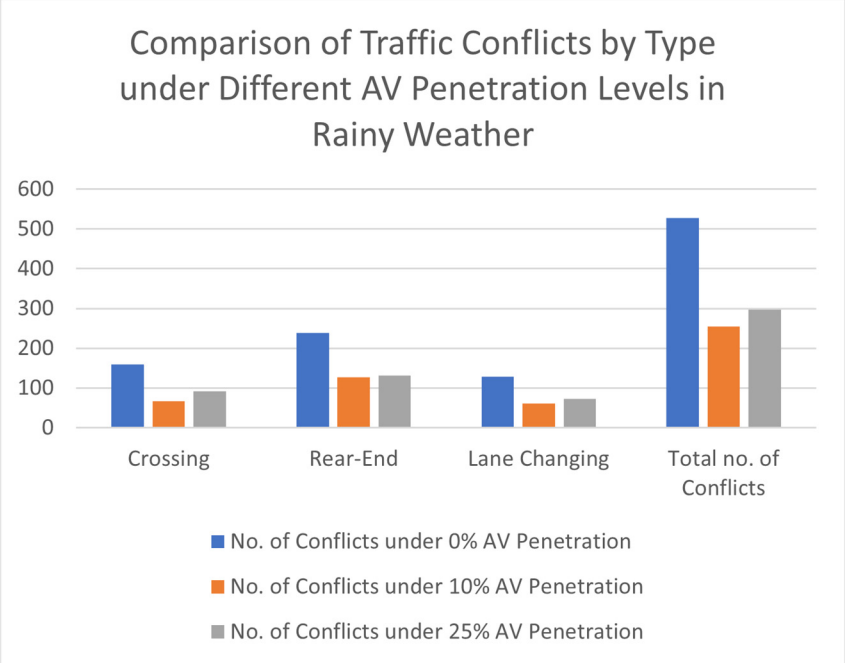


Figure 15. Graphical representation of the comparison of traffic conflicts under rainy weather conditions with 0%, 10%, and 25% AV penetration.

4.2.3. Snowy Weather Safety Performance

Under snowy weather conditions with 0% AV penetration, surrogate safety measures indicate the most challenging safety environment among all scenarios. Table 24a shows TTC, PET, and MaxDeltaV outputs while Table 24b shows the breakdown of traffic conflicts by type.

Under snowy weather conditions with 0% AV penetration, the mean TTC was 0.827 s (range: 0–1.5 s), reflecting the close vehicle interactions characteristic of snowy conditions. Such low values are common in snowy conditions, as reduced visibility and conservative driving behaviors limit available reaction time. The mean PET was 1.37 s (maximum: 4.70 s), indicating that while there is some spatial separation in conflicts, vehicle interactions remain

limited, especially at signalized intersections, where stopping and queuing are the primary behaviors. The mean MaxDeltaV was 4.09 m/s (range: 0.30–10.17 m/s), indicating that conflicts are of moderate severity, consistent with the effects of sudden speed changes.

Table 24. (**a**) Summary of surrogate safety measures at 0% AV penetration under snowy weather. (**b**) SSAM-based conflict statistics under snowy weather with 0% AV penetration.

(**a**)			
Measure	**Min**	**Max**	**Mean**
TTC (s)	0	1.5	0.827
PET (s)	0	4.70	1.37
MaxDeltaV (m/s)	0.30	10.17	4.09
(**b**)			
	Conflict Type		**No. of Conflicts**
	Crossing		201
	Rear-End		235
	Lane Change		117
	Total Conflicts		553

The total number of 553 conflicts recorded is the highest of all scenarios. The most frequent type of conflict was rear-end (235 conflicts), followed by crossing (201 conflicts) and lane-change (117 conflicts). The high number of rear-end collisions indicates that drivers have greater difficulty maintaining stable headways and smoothly decelerating in snow conditions. Thus, it can be concluded that, overall, the baseline scenario of snow with no AV penetration has the highest frequency of conflicts and increased conflict severity, highlighting the significant safety issues arising from adverse winter conditions at rural signalized intersections. Table 25a summarizes the surrogate safety measures at 10% AV penetration while Table 25b shows the breakdown of traffic conflicts by type.

Table 25. (**a**) Summary of surrogate safety measures at 10% AV penetration under snowy weather. (**b**) SSAM-based conflict statistics under snowy weather with 10% AV penetration.

(**a**)			
Measure	**Min**	**Max**	**Mean**
TTC (s)	0	1.5	0.73
PET (s)	0	4.6	1.16
MaxDeltaV (m/s)	0.13	12.21	3.73
(**b**)			
	Conflict Type		**No. of Conflicts**
	Crossing		72
	Rear-End		96
	Lane Change		55
	Total Conflicts		223

Under the snowy weather conditions with 10% AV penetration, the mean TTC decreased to 0.73 s (range: 0–1.5 s). Even though this value is lower than the baseline snow value, the drop does not indicate increased crash risk, as it represents more regular, stable car-following dynamics enabled by AVs in a mixed-traffic environment. Mean PET was 1.16 s (max: 4.6 s), suggesting that sufficient conflicts were achieved despite visibility challenges posed by snow-covered roads. Mean MaxDeltaV dropped to 3.73 m/s (range: 0.13–12.21 m/s), clearly signaling a reduction in conflict severity compared with its 0% AV.

A total of 223 conflicts were identified in the 10% AV snow scenario, representing a significant reduction from the 553 conflicts in the baseline condition. The types of conflicts showed similar patterns: rear-end (96 conflicts), crossing (72 conflicts), and lane-change (55 conflicts). The overall reduction in conflicts suggests the safety benefits that even a low-level penetration of AVs brings in snowy conditions. Table 26a summarizes the surrogate safety measures at 25% AV penetration while Table 26b shows the breakdown of traffic conflicts by type.

Table 26. (**a**) Summary of surrogate safety measures at 25% AV penetration under snowy weather. (**b**) SSAM-based conflict statistics under clear weather with 25% AV penetration.

(**a**)

Measure	Min	Max	Mean
TTC (s)	0	1.5	0.79
PET (s)	0	4.6	1.34
MaxDeltaV (m/s)	0.01	12.13	4.47

(**b**)

Conflict Type	No. of Conflicts
Crossing	119
Rear-End	162
Lane Change	87
Total Conflicts	368

Under snowy weather conditions with 25% AV penetration, the mean (TTC) increased further to 0.79 s (range: 0–1.5 s), indicating a longer time between car-following conflicts in mixed traffic. The mean (PET) also increased to 1.34 s, with a maximum of 4.6 s, the highest PET across all snow weather scenarios. This change reflects a more conservative gap in acceptance and a higher degree of separation at the point of conflict, even given the lack of visibility. The mean MaxDeltaV was 4.47 m/s (range: 0.01–12.13 m/s), slightly higher than that of the 10% AV case, though still comparable to or lower than snow condition baseline values.

A total of 368 conflicts were observed under the 25% AV snow scenario. This is a significant decrease from the baseline conditions (553 conflicts) but an increase from the 10% AV scenario (223 conflicts). Rear-end conflicts accounted for the majority (162), with crossing (119) and lane change (87) following. This indicates that while higher AV penetration rates lead to better gap acceptance and fewer crossing-related conflicts, rear-end and lane-change conflicts can still occur through mixed traffic interactions under signalized conditions. In summary, the 25% AV snow scenario improves conflict severity while maintaining safe interaction distances among vehicles. Figure 16 presents a comparison of the number of traffic conflicts by conflict type (crossing, rear-end, and lane-change) in snowy conditions for 0%, 10%, and 25% AV penetration rates.

4.2.4. Overall Comparison of Total Conflicts Across Weather and AV Penetration Levels

Table 27 summarizes the total conflicts across all weather and AV penetration conditions. In general, total conflicts consistently decreased with increased AV penetration across all weather conditions, although the level of influence may vary with weather severity.

For clear conditions, total conflicts dropped from 535 at 0% AV to 436 at 10% AV (≈19% drop), and then further to 368 at 25% AV (≈31% drop). This suggests that AV integration is effective at reducing conflict frequency even under ideal operating conditions.

For rainy conditions, conflicts dropped significantly from 528 at 0% AV to 255 at 10% AV (over 50% drop), and further to 297 at 25% AV, but remained well below the baseline.

This suggests that the greatest safety improvement (i.e., the fewest conflicts) when it rains occurs with minimal AV penetration.

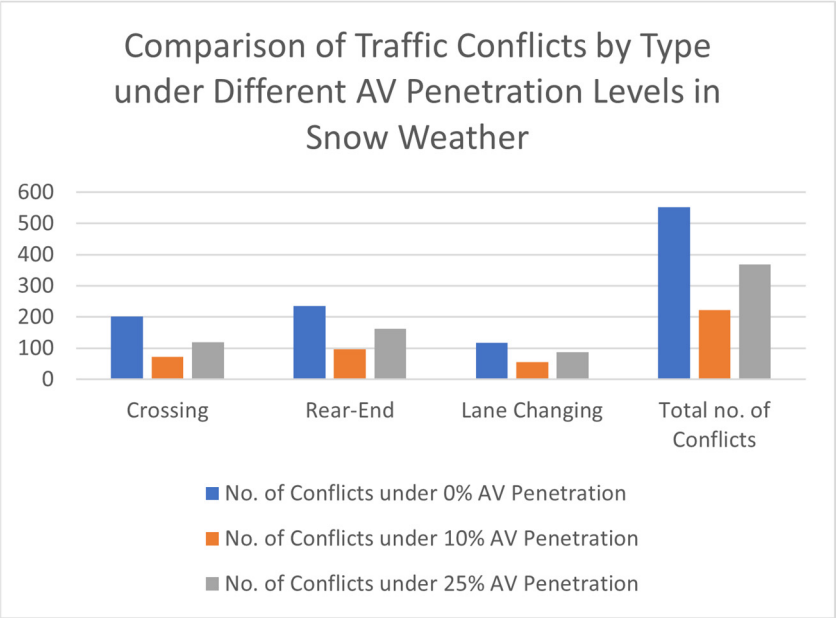


Figure 16. Graphical representation of the comparison of traffic conflicts under snowy weather conditions with 0%, 10%, and 25% AV penetration.

Table 27. Total number of traffic conflicts identified across clear, rainy, and snowy weather conditions under 0%, 10%, and 25% AV penetration levels.

Weather	AV %	Total No. of Conflicts
Clear	0%	535
Clear	10%	436
Clear	25%	368
Rain	0%	528
Rain	10%	255
Rain	25%	297
Snow	0%	553
Snow	10%	223
Snow	25%	368

For snowy conditions, the baseline scenario had the most conflicts overall (553 conflicts) and dropped substantially to 10% AV (223; ≈60% reduction). Increasing AV penetration to 25% resulted in more conflicts (368), but remained well below baseline, suggesting a continued safety benefit with AV integration.

An interesting observation is that the 10% AV scenario produced slightly fewer total conflicts than the 25% AV scenario under rainy and snowy conditions. This non-monotonic pattern likely reflects interaction effects between autonomous and human-driven vehicles in mixed traffic environments. At relatively low AV penetration levels, autonomous vehicles can help stabilize traffic flow through smoother acceleration and more consistent car-following behavior, which may reduce potential conflict opportunities. As the share of AVs increases within a mixed traffic stream, interactions between AVs and human-driven vehicles can introduce more varied driving responses, particularly under adverse weather conditions. These interaction effects may lead to localized variations in speeds and queue dynamics, which can slightly influence the frequency of conflicts observed at the intersection under mixed traffic conditions.

5. Conclusions

This study evaluated the mobility and safety impacts of low autonomous vehicle (AV) penetration at a rural signalized intersection under clear, rainy, and snowy weather conditions using a microsimulation-based framework. The results show that AV integration provides the most pronounced mobility benefits under clear weather, where 10% AV penetration led to noticeable increases in average approach speeds and modest reductions in vehicle delay and travel time, while higher penetration levels (25%) produced smaller incremental gains, indicating diminishing returns under signal-controlled operations. Under rainy and snowy conditions, overall mobility performance was largely governed by adverse weather effects and signal control constraints; however, limited but measurable mobility improvements were still observed, particularly at higher AV penetration levels on select approaches, suggesting that AVs can partially stabilize traffic flow even under unfavorable conditions.

In contrast to mobility, safety performance improved consistently across all weather scenarios. Total traffic conflicts were substantially reduced at 10% AV penetration under clear, rainy, and snowy conditions, with reductions ranging from approximately 19% to nearly 60% relative to baseline traffic. Although conflict reductions were less pronounced at 25% AV penetration under adverse weather, safety performance remained significantly better than the non-AV scenario, supported by higher PET values and lower MaxDeltaV, indicating improved spatial separation and reduced conflict severity. Overall, the findings suggest that low AV penetration levels (around 10%) offer the most reliable near-term benefits, delivering meaningful safety improvements and modest mobility gains even under rain and snow, while higher penetration levels yield diminishing mobility returns in weather-constrained, mixed traffic environments.

From a practical perspective, these findings suggest that even early stages of AV adoption can provide measurable safety benefits at rural signalized intersections, particularly through reductions in traffic conflicts and improvements in conflict severity indicators. For rural transportation agencies, this indicates that mixed traffic environments with relatively low AV penetration may still contribute to safer intersection operations. While the exact operational thresholds may vary depending on site-specific traffic demand and signal control conditions, the results provide an initial indication that AV penetration levels around 10% may already produce meaningful safety improvements while maintaining stable mobility performance.

Author Contributions: The research was conceptualized by T.A., Y.H. and P.L.; methodology, T.A. and Y.H.; software, T.A.; validation, T.A.; formal analysis, T.A.; investigation, T.A.; resources, Y.H. and P.L.; data curation, T.A. and Y.H.; writing—original draft preparation, T.A.; writing—review and editing, T.A., P.L. and Y.H.; visualization, T.A.; supervision, Y.H. and P.L.; project administration, Y.H. and P.L.; funding acquisition, P.L. and Y.H. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data will be made available upon request.

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