Hindawi
Journal of Advanced Transportation
Volume 2021, Article ID 6677010, 16 pages
https://doi.org/10.1155/2021/6677010

Research Article

Studying the Simultaneous Effect of Autonomous Vehicles and Distracted Driving on Safety at Unsignalized Intersections

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Received 14 November 2020; Revised 11 April 2021; Accepted 16 June 2021; Published 25 June 2021

Academic Editor: Mehdi Nourinejad

Human error is one of the leading causes of accidents. Distraction, fatigue, poor visibility, speeding, and other such errors made by drivers can cause accidents. With the rapid advancements in automation technologies, transportation planners have strived to use Intelligent Transportation Systems (ITS) to minimize human error. In this study, the effect of Autonomous Vehicles (AVs) on the number of potential conflicts at two unsignalized intersections is investigated by using a microsimulation model in PTV Vissim software. For human-driven cars, the factor that is considered for calibration is driver distraction mainly caused by reading or writing text messages on a cellphone while driving. This factor can be estimated using driving simulators. In this paper, five different scenarios were defined for simulation, in addition to the primary state, according to the different market penetration rates of AVs in Vissim. Safety assessment was performed by the Surrogate Safety Assessment Model (SSAM) using Time to Collision (TTC) and Deceleration Rate to Avoid Crashes (DRAC) indicators to determine the number of accidents. It was concluded that the presence of 100% of AVs could reduce the potential for accidents by up to 93%.

1. Introduction

An autonomous vehicle (AV) does not require direct driver intervention for certain functions such as steering control, acceleration, and braking. The Society of Automotive Engineers (SAE) has introduced six levels of driving automation. These levels start at zero, where no assistance is provided to the driver, and ends at level 5, where the driver does not interfere with driving at all [1]. Levels 1 and 2 technologies are currently available, and levels 3 to 5 are being tested [2]. According to Litman [3], in the 2050s, almost half of the vehicles sold will be AVs, and 40% of the trips could be autonomous. There are many benefits of using autonomous vehicles, including reduced travel time, lower travel costs, reduced emissions, better fuel consumption, and improved traffic safety. AVs also allow people who cannot drive to use their vehicles [3].

One of the main causes of vehicle crashes is human error [4]. According to the Road Safety Association, more than 90 percent of car accidents are caused by human error, including driver fatigue, distraction, and loss of consciousness. Results of a study show that AVs can decrease the rate of accidents and insurance costs by 90% [5]. Nevertheless, this research has overlooked some points. For instance, the investigations by Kalra and Groves [6] show that if the automation technology increases total vehicle travel, net safety gains can substantially decline. Furthermore, confidence in automation may discourage drivers from paying attention to the road. Thus, to better understand such effects, trip, mode, and route choice models should be revised to include the impacts of autonomous vehicles on safety [2]. In addition, as more automation techniques are used, different errors (e.g., exposure of AVs to cyber threats and the loss of sensor functionality in adverse weather conditions) can be generated. If such errors are not aptly managed, they may cause critical safety problems [3]. So, it is essential to further investigate the influence of AVs on safety before their presence in transportation networks.

This study addresses the effects of AVs with different conditions (i.e., various penetration rates and total

demands) on the number of accidents at two unsignalized intersections compared to the normal condition which has just human-driven cars alongside the real-world demand. For a better understanding of the behavior of human-driven cars that interact with AVs in different scenarios, driver distraction, which is one of the leading causes of accidents, is calibrated. Also, in order to evaluate the quality and efficiency of the research model, the autonomous vehicles simulated by the two European projects are compared with each other. The most prominent motivation for this comparison is to determine which of these two AV projects can better interact with conventional vehicles in terms of safety.

The remainder of this paper is organized as follows: The next section contains existing literature on AV simulation for safety assessment, and the novelty of this research is presented. A detailed explanation of case studies, the behavior of AVs for the simulation, the sensitivity analysis and calibration process, the definition of simulation scenarios, and the safety assessment follow next. The fourth section of the paper shows the results obtained from the simulation in conjunction with a comprehensive discussion. Finally, the last part sums up the conclusions of the study.

2. Literature Review

This section provides a review of several research studies that have investigated the safety effects of AVs or Connected and Autonomous Vehicles (CAVs) using various methods. A study by Morando et al., which was conducted at the University of Monash, Australia, is the first comprehensive study on the impact of autonomous vehicles on traffic safety [7]. Morando used the Vissim software to simulate AVs and examined the potential for accidents with the Surrogate Safety Assessment Model (SSAM). He simulated five scenarios of 0%, 25%, 50%, 75%, and 100% presence of AVs in the network in Vissim, and showed that by increasing the penetration rate of AVs, the average number of accidents in the studied segment significantly decreased. The simulation was performed for both roundabout and signalized intersections.

Furthermore, in a study by Tibljaš et al. [8], the effect of autonomous vehicles on the safety of four famous roundabouts in Croatia is examined. A simulation was performed using Vissim output in the SSAM software. The severity of accidents was determined by using the Time to Collision (TTC) rate of each collision, and the speed difference between the two vehicles. One of the innovations of this research is using equation (1) which can predict the number of accidents per year through the number of possible collisions:

$$\frac{\text{crash}}{\text{year}} = e^{\beta_0} \times \log\left(\frac{\text{conflict}}{\text{hour}}\right)^{\beta_1}, \tag{1}$$

where β_0 and β_1 should be obtained from network calibration.

Besides, Papadoulis et al. [9] introduced a new algorithm for autonomous driving. This algorithm has two main bases, longitudinal control, and lateral decision-making, through which a car can find its near vehicles and recognize the adjacent AVs. It then receives the necessary information from them. Like the Morando study, five different scenarios for the market penetration rates of AVs were defined and simulated in the Vissim software to test this algorithm for different traffic conditions. Papadoulis noted that potential collisions would be reduced by 90 to 94 percent with a 100 percent penetration rate for AVs on the network. Similarly, Virdi et al. [10] developed a custom algorithm called "Virdi CAV Control Protocol (VCCP)" to account for the behavior of CAVs. The results of this study show that in the low percentages of CAVs at signalized intersections, the number of potential collisions increases. This can be addressed as being the outcome of more hazardous driving by conventional cars in the "dilemma zone," possibly reducing safety for CAVs at low headways. However, at unsignalized intersections, from the very beginning of the penetration of CAVs, there is a significant reduction in the number of accidents.

Moreover, Rahman et al. [11] have examined two types of vehicles. The first type includes those cars that are only connected and transfer information among each other. The second type comprises low-level autonomous vehicles, which, in the not-too-distant future, will occupy a high percentage of roads. In this research, two main features of these cars, namely, smart braking and deviation avoidance system, have been investigated. The Vissim software was used for modeling each of these vehicle types. For the first type, the Intelligent Driver Model, and for the second type, the Bando model was used to simulate driver behaviors. It is observed that by increasing the penetration rate of AVs, the rate of cross-sectional accidents decreases. However, for a road segment, at least 30% of AVs are required to see significant changes in reducing the number of accidents.

Also, Mousavi et al. [12] examined the effect of autonomous vehicles on the safety of an unsignalized three-way intersection at the various levels of service. The simulation was supported by the Vissim software, and safety analysis was performed through SSAM and TTC measurement. Estimates demonstrate that autonomous vehicles have the potential to reduce the number of total conflicts near the intersection either on minor streets or on major arterials.

Finally, two types of AVs (low and high automation levels) were considered by Arvin et al. [13] for simulation. The Wiedemann car-following model was used for autonomous vehicles with low automation levels, and the Adaptive Cruise Control (ACC) model was used for highly automated vehicles. The simulation was performed in open-source software called VENTOS. The outputs produced by the software were used to calculate the TTC from which the number of conflicts can be extracted. In addition to the fact that the simulation software in this study is different, another indicator for safety assessment, namely, "driving volatility," was introduced. The study also found that the number of accidents was significantly reduced as the number of AVs increased.

One of the shortcomings of previous studies is that the behavior of human-driven cars has not been modeled precisely under mixed traffic conditions, and some parameters which may significantly influence final results have

been ignored or their values have just been assumed for the simulation process. In other words, the main contribution of earlier research works in this field has been just the development of AV behavior modeling without paying painstaking attention to the sensitive characteristics of human-driven cars like driver distraction which can considerably change the number of simulated accidents. In this study, we try to fill this gap by the accurate determination of driver distraction as the input for the driving behavior of conventional vehicles in Vissim. Moreover, this paper proposes a combination of two conflict indicators for the safety assessment, which can lead to more accurate findings.

3. Methodology

In this study, we simulate the desired transportation network using the Vissim software and enter the autonomous vehicles based on the scenarios that will be explained. Then, we determine the effect of AVs on the safety of the studied section using SSAM.

3.1. Data Collection. This research focuses on unsignalized intersections because these intersections can often pose many safety hazards due to drivers' noncompliance with the defined hierarchy of movements. Furthermore, few studies have been done on such intersections.

3.1.1. Characteristics of the Section under Study. Three major points were considered for choosing a desirable intersection. First, the conflict areas should have been numerous for the intersection. Second, vulnerable road users should have been sparse in the intersection because we just want to assess the number of conflicts between two vehicles. Finally, driving offenses and erratic movements of drivers should have been rare. Hence, the findings of this study can only be generalized for other intersections with similar geometry alongside the satisfaction of these three conditions. The following intersections were selected for this research based on the aforementioned conditions, and the traffic volumes were collected at each intersection using a video camera on Monday, November 11, from 7 pm to 8 pm (the peak daily hour at these two intersections), as shown in Figures 1 and 2.

(1) Vesal Shirazi-Bozorgmehr Intersection. This unsignalized intersection is located in the center of Tehran, and both of its streets are two-way. Vesal Shirazi Street has a collector/distributor functional classification with a maximum speed of 50 km/h, and Bozorgmehr Street has a local street functional classification with a maximum speed of 40 km/h. Vesal Shirazi has two lanes in each direction with a width of 3.5 m. Bozorgmehr Street also has one lane in each direction.

(2) Sattarkhan-Niroo Intersection. This unsignalized intersection is located in the west of Tehran with flashing lights control. Sattarkhan is an arterial street with a maximum speed limit of 60 km per hour. This street has three lanes in each direction. Niroo is a one-way street with a width of 3.5 m intersecting Sattarkhan Street at an angle.

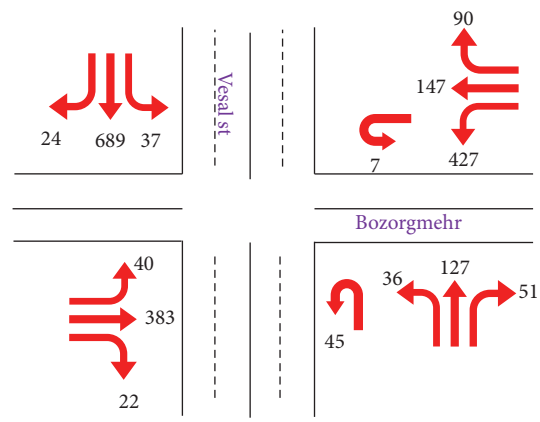

Figure 1: Vesal-Bozorgmehr intersection with passing volumes at the peak hour (vehicle per hour).

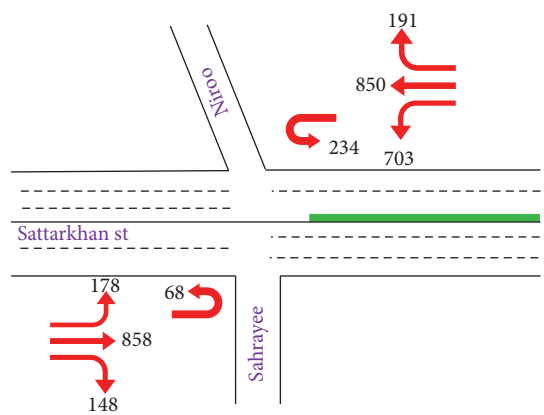

Figure 2: Sattarkhan intersection with passing volumes at the peak hour (vehicles per hour).

3.1.2. Initial Inputs of Vissim. The passing volumes were entered with the values shown in Figures 1 and 2 for each intersection in the Vehicle Input section of the Vissim software (with the consideration of one percent for heavy vehicles). For Vesal Shirazi Street, a uniform speed distribution was assumed [7] with a minimum of 40 and a maximum of 50 km per hour. On the other hand, the minimum value of 30 and a maximum of 40 km per hour were considered for Bozorgmehr Street. Also, for Sattarkhan Street, it was assumed that the uniform speed distribution is between 40 and 60 km per hour. These values, which were consistent with field observations, were entered into the software at the desired speed section.

3.2. Driving Behavior in Vissim. The car-following model is the most significant part of a simulation study for drivers' behavior in Vissim. Few studies could be found that have overlooked these parameters for calibration and sensitivity analysis. However, the parameters of the lane changing behavior section usually affect freeway and highway characteristics. Also, the parameters in the traffic signal section are used for signalized intersections, which are insignificant in this study.

The default Vissim car-following model is based on the Wiedemann car following logic [14], of which two different types are provided by this software: Wiedemann 1974 for modeling urban conditions and Wiedemann 1999 for modeling freeway conditions. In this study, the Wiedemann 74 model was used to simulate the behavior of human drivers, as well as the Wiedemann 99 model to implement the behavior of AVs, because this model considers behavioral characteristics in more detail than the Wiedemann 74.

The Wiedemann 74 model consists of three parameters [15]:

(i) Average standstill distance (ax or w1): the average desired distance between two vehicles when stopping. Its default value in the software is 2 m.

(ii) Additive part of safety distance (bx_{add} or w2): this value is used to calculate the safety distance of vehicles from each other, with a default value of 2.

(iii) Multiplicative part of safety distance (bx_{mult} or w3): this parameter is used to calculate safety distance as well, and its default value is 3.

Wiedemann 99 also has ten parameters from CC0 to CC9. PTV Vissim User Manual provides more information on these parameters.

One parameter that has a significant impact on the occurrence of accidents is distracted driving, which remains understudied in previous research and not many studies have considered its implementation in such microsimulation software as PTV Vissim. Usually, the probability of driver distraction is deemed to be zero, which is often not the case. So, we will take a look at this parameter for a more accurate simulation of human-driven cars in this research.

3.2.1. Driver Distraction. Driver distraction is one of the most critical safety issues in the transportation network as engaging in other tasks while driving increases the risk of accidents. Although this factor is not usually considered when recording accidents, according to a National Highway Traffic Safety Administration (NHTSA) report, 10% of fatalities and 17% of injuries were caused by driver distraction in 2011 [16].

To enter this parameter into the Vissim software, three items need to be specified:

(1) The probability of distraction: this means the probability of the driver losing focus while driving and being unaware of driving conditions.

(2) Distraction duration distribution: the temporary period during which the drivers are distracted and then regain their focus.

(3) Lane angle distribution: the amount of the driver's deviation angle from the direct route during the period of distraction.

Items 2 and 3 should be calculated for drivers, and item 1 should be obtained from network calibration.

A survey of previous studies [17] reveals that the use of driving simulators is one of the most common methods for measuring driver distraction and other human factors. Moreover, the leading cause of distraction for most drivers is the use of cellphones while driving [18]. Thus, the use of mobile phones while reading or writing text messages was selected as a distraction source for this study, which can be assessed by using a driving simulator.

The purpose of the NHTSA [19] is to provide practical information on driver distraction caused by reading or writing messages while driving. To this end, 28 drivers were selected to participate in the study. They drove in a virtual environment with a driving simulator. Messages were sent to them from easy to difficult and drivers had to respond to messages while paying attention to road conditions. Then, the time which they look at the cellphone was extracted and the necessary statistical analysis was conducted on this glance time.

In the current study, 20 randomly selected male and female drivers participated. They ranged in age from 18 to 50 years. The drivers' faces were filmed by a camera while they were driving. The camera was located out of drivers' vision area. So, they could not be distracted by this device. Then, predetermined questions were sent to the drivers via mobile messaging and the drivers had to answer the questions while following the route. These questions included a variety of visual distractions, such as looking at a cellphone, writing a text message on a cellphone, and engaging in mental workload. After experimenting, the videos were analyzed to obtain the results. Given that drivers' distraction times were too short, it was essential to watch the videos at a playback speed rate of 0.25x to boost the accuracy of the analysis. The videos were played at the specified rate, and when the driver was distracted while driving, a lap button was pressed on a stopwatch, and when the driver looked back at the road, the next lap was recorded on the stopwatch. The time difference between two consecutive laps can be defined as the temporary distraction time of the driver. Drivers' blinking, the duration of which was less than 0.5 seconds, was not considered as distraction time. Accordingly, these values were omitted from the final results. The values of the cumulative probability of distraction time are given in Table 1.

The above distribution has been entered into the Vissim software for distraction time.

Another parameter required for the Vissim software to simulate driver distraction is the angle of deviation from the route during the distracted driving, which can be calculated by the outputs obtained from the simulator. It can be observed that angles of more than 15 degrees are related to situations where the driver is turning left or right. So, these values have been omitted from the outcomes. Finally, the values of the cumulative probability of lane angles are obtained in Table 2. The results of this section are entirely consistent with studies conducted in this field [20].

After extracting these two parameters and entering them into Vissim for the behavior of conventional vehicles, sensitivity analysis had to be performed for the probability of distraction. As it will be mentioned in section 3.4, driver distraction is important in assessing the safety of the intersection.

Table 1: The summary of calculated values for distraction time of the random sample.

Distraction time (seconds)	Cumulative probability (%)
0.64	11
0.74	20
0.86	30.5
0.97	40.2
1.1	50.6
1.25	60.3
1.44	70.3
1.72	80.2
2.31	90
7.34	100

Table 2: The summary of calculated values for the lane angle of the random sample.

Angle in degrees	Cumulative probability (%)
1.18	10
1.37	20.2
1.62	29.7
1.91	40.1
2.32	49.4
2.9	59.3
3.91	70.9
5.5	81.4
8.5	90.7
15	100

3.2.2. Autonomous Driving. Numerous studies have been conducted on the simulation of autonomous vehicles, including [21–23], and the characteristics of their traffic flow and driving behavior have been calculated through various tests. Autonomous vehicles have some common characteristics which should be considered for the simulation:

(1) AVs can keep a shorter headway than human-driven cars [21, 23]. It is possible to modify this feature in the Vissim software by changing the CC1 parameter in the Wiedemann99 car-following model.

(2) AVs accelerate more smoothly and faster than conventional vehicles from a standstill [24]. To model this feature in Vissim, CC8 and CC9 values must be modified in the Wiedemann99 model.

(3) During free flow, AVs keep their speed constant without any oscillation [25]. As such, they have a smaller speed range [21]. For the Vesal-Bozorgmehr intersection, conventional vehicles on Vesal Street had a uniform speed distribution between 40 and 50 km/h, which would be 44–46 km per hour for AVs with the same average as for the base model (45 km/h), but in a narrower range. For Bozorgmehr Street, the speed range of AVs was set from 34 to 36 km per hour. Speed distribution for these vehicles at the Sattarkhan-Niroo intersection was in the range of 54–56 km/h.

(4) These cars do not let the space between themselves and the front vehicle increase, and they follow their path with the smallest distance oscillation possible [10, 23]. To implement this feature, the CC2 parameter must be revised.

(5) If the vehicles are connected, they communicate with each other using CACC technology and form platoons [26]. This feature can be accessed in the Autonomous Driving subsection under Driving Behavior in Vissim. Doing a sensitivity analysis of the parameters in this section, it was observed that this factor does not have a significant effect on the studied intersections and, as expected, it seems to be effective only on highways and freeways.

(6) AVs can change lanes accurately at the right speed. To achieve this capability, both the features of cooperative lane change and the maximum speed difference of the vehicles need to be modified [27].

(7) For AV vehicles, each specific speed has an absolute acceleration and deceleration rate [26]. The acceleration function of the vehicles needs to be changed so that, unlike conventional vehicles, all three values of the maximum, minimum, and average acceleration are equal at the same speed. Figure 3 represents the aforementioned subjects better.

(8) Another point to consider regarding AV simulation is the desired distance between cars. If a conventional car is driving in front of an AV, the applied distance is greater than when an AV is following another AV due to slower human reaction time. As can be observed in Figure 4, the distance between two CAVs has the smallest value, which increases the network capacity [7, 22]. Also, the distance between a CAV and a human-driven car (HV) has the largest value.

In this research, we will use two different projects by European companies for AV simulation, and compare their safety impacts in order to determine the project that can better interact with human-driven cars:

(i) The Coexist project [28] is a European study that began in May 2017 and aimed to prepare the international community for the advent of autonomous vehicles in cities. Many organizations are involved in the project, including PTV, Renault, and several universities. The project has been put into operation in four cities (Milton, England; Stuttgart, Germany; Helmond, the Netherlands; and Gothenburg, Sweden). The characteristics of autonomous vehicles have been gained from various experiments and can be used as default AV driving behaviors in Vissim. Coexist tested its cars with four driving patterns:

(1) Rail Safe: for cars with this type of behavior, exclusive lanes are considered at a great distance, and lane changing is not allowed. Besides, the

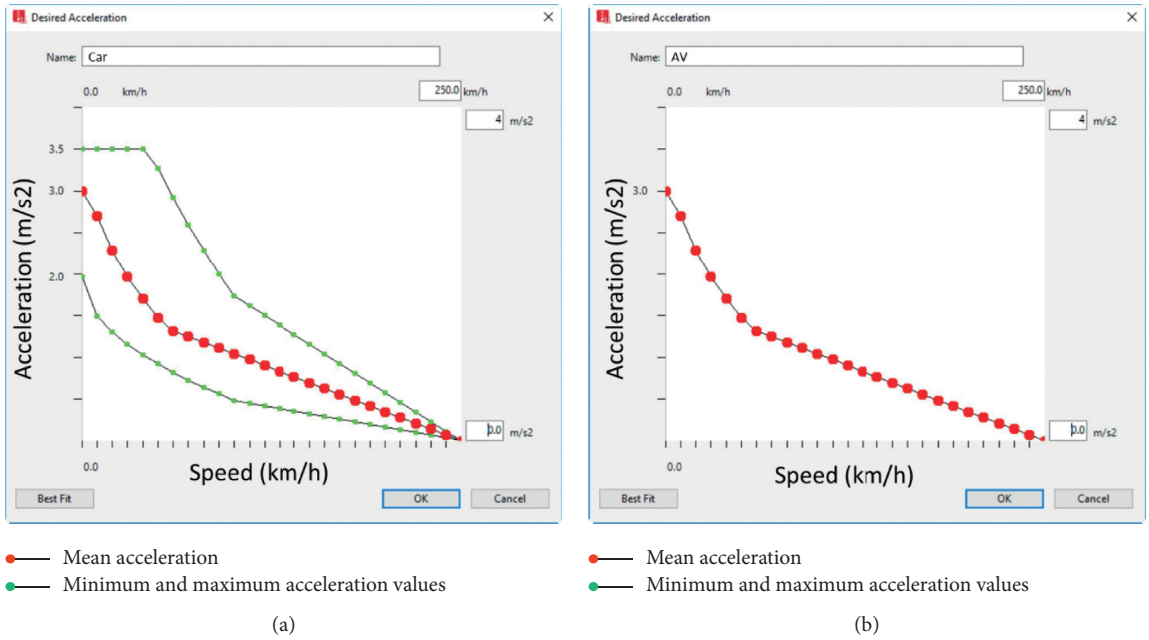

Figure 3: Desired acceleration functions of a typical car and an autonomous vehicle in Vissim [15]. (a) Typical car. (b) Autonomous vehicle.

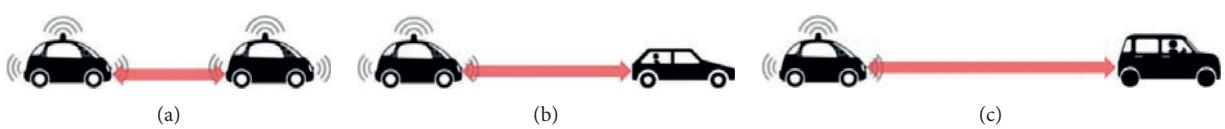

Figure 4: The relative implemented distance between a CAV and (a) CAV, (b) AV, and (c) HV [28].

brick wall stop is always active for them. This pattern is not applicable to unsignalized intersections.

(2) Cautious (first generation of Highly Automated Vehicles): the vehicle continuously pays attention to the information that is transmitted to it from other vehicles and traffic components, and it makes a safe condition for its passengers. Its brick wall stop is active. This pattern could also be used in an unsignalized intersection, and lane changing is feasible in this type of behavior.

(3) Normal (second generation of HAVs): the vehicle acts as a conventional car, except that it recognizes the ability to estimate the distance and speed of its surrounding vehicles via sensors and executes the necessary action.

(4) All-Knowing (third generation of HAVs): the car has a very high level of awareness, which allows it to accept smaller distances.

The main difference between these AV types is their ability to accept headways and the safety distance. Cautious AVs are more conservative than human-driven cars. Therefore, they accept greater headways in comparison with other AV types. All-Knowing AVs can behave more aggressively and have enough courage to keep smaller headways compared to cautious and normal AVs.

(ii) The idea for the UK Autodrive project [29] was formed in December 2014 and began with the aim of introducing driverless cars to the UK Transport Network. Many companies are involved in the project, the most important of which are Ford, Jaguar, and the University of Cambridge. Asadi et al. [25] simulated this type of vehicle in the Vissim software and achieved the results presented in Table 3 for the parameters of driving behavior.

In light of the foregoing discussion, the driving behavior parameters for all three generations of AVs in Coexist and UK Autodrive projects are presented in Table 3. Also, the acceleration functions were modified according to Figure 3.

3.3. Introducing SSAM [30]. SSAM is a software package developed by the Federal Highway Administration (FHWA) to analyze the output of vehicle trajectories from various microsimulation software, such as VISSIM, AIMSUN, and PARAMICS. There are three types of conflicts in SSAM to evaluate the traffic conflicts observed in the simulation: Rear-End, Crossing, and Lane Change. The method of assigning each conflict to each of these three types is as follows:

Table 3: The value of the AVs' driving behavior parameters compared to Vissim defaults.

	Parameter		Coexist			UK Autodrive		
		Human-driven car	Cautious AV	Normal AV	All-knowing AV	Cautious AV	Normal AV	All-knowing AV
Car following parameters	CC0	1	1.5	1.5	1	1.5	1	1
	CC1	0.9	1.5	0.9	0.6	1.5	0.9	0.5
	CC2	4	0	0	0	0	0	0
	CC3	−8	−10	−8	−6	−8	−8	−8
	CC4	−0.35	−0.1	−0.1	−0.1	0	0	0
	CC5	0.35	0.1	0.1	0.1	0	0	0
	CC6	11.44	0	0	0	0	0	0
	CC7	0.25	0.1	0.1	0.1	0.15	0.25	0.45
	CC8	3.5	3	3.5	4	3.3	3.5	3.9
	CC9	1.5	1.2	1.5	2	1.3	1.5	1.9
Following parameters	Max look back distance	150	150	150	150	800	800	800
	Max look ahead distance	250	250	250	300	800	800	800
Lane change parameters	Safety distance reduction factor	0.6	1	0.6	0.75	0.8	0.6	0.3
	Cooperative lane change	No	No	Yes	Yes	Yes	Yes	Yes
	Maximum speed difference	—	—	10.8	10.8	10.8	10.8	10.8
	Maximum collision time	—	—	10	10	10	10	10

First, the collision angle between the two cars at risk is calculated. This angle is the one created between the trajectory of the first car and the second car at the collision point. The collision angle is then used to classify the following types of accidents:

(i) Rear-End conflict: collision angle less than 30 degrees

(ii) Lane Change conflict: collision angle between 30 and 85 degrees

(iii) Crossing conflict: collision angle more than 85 degrees

Figure 5 depicts these definitions in more detail.

Two surrogate measures for safety analysis can be set in this software:

(1) Time to Collision (TTC): this indicator was first proposed by Hayward [31], who described a TTC event as "time remaining until a collision occurs if the current path and the speed difference between the two vehicles are maintained." This measure can be calculated using the following equation:

$$\mathrm{TTC} = \frac{x_L - x_F - L}{v_L - v_F}, \quad \text{if } v_F > v_L, \tag{2}$$

where x_L and x_F are the locations of the leading vehicle and following vehicle, respectively; L is the length of the leading vehicle and v_i is the corresponding speed of the vehicle. The default value of TTC in SSAM is 1.5 seconds, and its maximum value can be 5 seconds.

(2) Post-Encroachment Time (PET): this measure is defined as the time difference between the moment the offending vehicle passes through the potential collision area and the moment of entry to this area by the vehicle that has the right of way [32].

$$\mathrm{PET} = t_F - t_L, \tag{3}$$

where t_F is the passing time of the following vehicle through the collision point and t_L has the same definition but for the leading vehicle. The default value of this indicator in SSAM is 5 seconds, and its maximum value is 10 seconds.

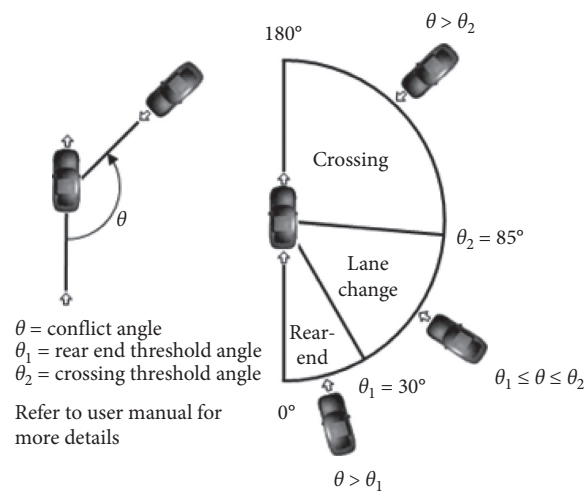

Figure 5: Classification of conflict type in SSAM [30].

3.4. Sensitivity Analysis. In this study, a sensitivity analysis was performed on most of the parameters based on the study by Habtemichael and Santos [33]. First, we executed the default mode to the required number of runs. The number of executions needed to determine the four measures of

performance in this study (total conflict number, Rear-End, Crossing, and Lane Change conflicts), according to Truong et al. [34], was equal to 15 for both intersections. Then, we obtained the outputs related to the performance measures from the software. Next, we changed the value of one of the driving behavior parameters and compared the new results with the default results using a t-test and considering a 95% confidence level. If the obtained P value is less than 0.05, it can be concluded that the effect of the applied change is significant; otherwise, the change is not significant. The parameters that are effective in determining the passing volume were all the parameters of the car-following model (w1 to w3), also the parameter of "Safety Distance Reduction Factor" at the Sattarkhan intersection. The effective parameters in cross-sectional safety assessment were average standstill distance (w1), the probability of distraction, and TTC.

3.5. Calibration

3.5.1. Stage 1. At this stage, an attempt was made to bring the simulated passing flow of the vehicles as close as possible to the volume observed in the video. The difference between the two values in traffic engineering is measured by the GEH index.

$$\mathrm{GEH} = \sqrt{\frac{(E-V)^2}{(E+V)/2}}. \tag{4}$$

In this equation, E is the output passing volume from Vissim, and V is the observed volume.

The value of this index for all movements should be less than 10, and also 85% of GEHs should be less than 5; otherwise, this criterion rejects the constructed model, and the sensitive parameters in determining the passing volume must be changed until this criterion is accepted. For Vesal Shirazi intersection, values 1, 1.5, and 2.5, respectively, for the w1 to w3 parameters caused all GEHs to be less than five and their maximum to be 2.1 for all 15 runs. At the Sattarkhan intersection, with values of 0.75, 1.5, and 2.5 for w1 to w3 and 0.3 for the safety distance reduction factor, all GEHs were less than 5 and the maximum was 2.5. Therefore, the initial calibration of both intersections was performed.

3.5.2. Stage 2. For this stage, the performance measure of the study had to be determined. Since the goal of this study was to determine the four cases (total conflict number, number of rear-end, crossing, and lane change conflicts), we calibrated these values.

The Mean Absolute Percentage Error index (MAPE) was used to predict the accuracy of the model, which is used at this step of the calibration. The relationship of this index is as follows:

$$\mathrm{MAPE} = \frac{1}{n}\sum_{i=1}^{n}\frac{|x_i - y_i|}{y_i}. \tag{5}$$

In this equation, x_i indicates the number of simulated conflicts evaluated by the software, and y_i shows the number of actual and counted conflicts in the videos. Also, n is the number of traffic microsimulation runs.

For each intersection and each collision type, we calculated the value of MAPE. If the value was less than the acceptable error defined for the research (15%), we accepted the model for all four performance measures. Otherwise, we made changes to important parameters (TTC and distraction probability) to achieve the desired result.

The research of Huang et al. [35] is one of the most comprehensive studies in this regard, in which the potential for the occurrence of accidents at ten signalized intersections has been calculated and then calibrated using the MAPE criterion. In this study, Huang has defined the three main categories of collisions, which are precisely the ones that appear after entering the Vissim outputs into the SSAM software. According to Huang's definitions for each intersection, collision avoidance maneuvers were counted depending on the type of possible conflict. Then, according to the videos recorded from the intersections, MAPE was calculated for each type of collision using equation (5).

Finally, by changing the significant parameters at this stage, for Vesal Shirazi intersection, the probability of distraction of 15%, and TTC = 1.5 seconds, led to MAPEs of 4.7%, 7.5%, 5.5%, and 13.8% for total, rear-end, crossing, and lane change conflicts, respectively. For the Sattarkhan intersection, a 40% chance of distraction and a TTC = 1.8 seconds led to 4.6%, 9.8%, 5.8%, and 10% MAPEs, indicating that both intersections meet all performance criteria and are calibrated in the base model.

3.6. Simulation Scenarios. Asadi et al. [25] thoroughly address the approximate presence time of each AV generation, which is presented in Table 4. Although these predictions may be optimistic, it can be argued that the overall forecast trend is accurate and only the start year of the presence of AVs maybe 10 to 20 years later than the scenarios presented. In this case, it comes very close to the predictions offered by Litman [3].

It is essential to perform the sensitivity analysis on various parameters to achieve more precise and comprehensive results. Hence, several simulation scenarios were defined in this research. Different vehicle compositions shown in Table 4 were the first set of considered scenarios. Moreover, two different AV projects (Coexist and UK Autodrive) whose detailed characteristics have been depicted in Table 3 were analyzed and compared in this study. Finally, three scenarios for the total demand were designated. The first scenario has real-world demands, which can be observed in Figures 1 and 2, and two other scenarios were uncrowded and overcrowded conditions, which have demands equal to 0.8 and 1.2 of normal traffic volumes, respectively. Therefore, 36 simulation scenarios (6 different vehicle compositions × 2 AV behaviors × 3 total demands) existed in this paper for each case study. We ran the Vissim software for calibrated intersections 15 times and received safety outputs for each scenario. In the following sections, we will discuss the safety assessment and the conclusion.

Table 4: Vehicle composition for each scenario of this study.

Year	Human-driven car	Cautious AV	Normal AV	All-knowing AV
2020	100%	—	—	—
2030	90%	10%	—	—
2035	70%	10%	20%	—
2040	37%	8%	45%	10%
2045	20%	—	40%	40%
2050	—	—	30%	70%

3.7. Safety Assessment. The "Traffic Conflict Technique" is widely utilized for traffic safety analysis. One of the advantages of these indicators is their ability to obtain collision severity in a short period compared to real accident data. Also, the use of traffic conflict as a surrogate measure of safety makes it possible to predict accidents before they occur and to prevent related damages [36].

To measure these conflicts, some indicators are used on which extensive studies have been conducted in recent decades:

(1) Time to Collision: this indicator, as described in the previous sections, is one of the integral components of traffic safety assessment, and many studies, including [7, 9, 35], have used this indicator.

(2) Postencroachment Time: this measure has also been used in studies such as [37, 38]. According to Archer and Kungl [39], the PET concept is used only to measure important safety events where there are crossing ways (e.g., intersections). The TTC is used to estimate events where cars have similar routes (such as rear-end collisions).

(3) Deceleration Rate to Avoid Crashes (DRAC): this parameter was first defined by Almqvist et al. [40] regarding the role of the speed difference and braking rate in potential collision occurrences. The DRAC is the speed difference between the following vehicle and its corresponding leading vehicle, divided by the time they are approaching. In other words:

$$\mathrm{DRAC} = \frac{(v_F - v_L)^2}{2(\Delta x - L)}, \tag{6}$$

where the definition of these parameters is similar to equation (3).

The study by Cunto and Saccomanno [41] provides a systematic method of calibrating microsimulation models based on safety performance. Safety performance has been defined in terms of potential conflict measurement, which is related to the DRAC with the Maximum Available Deceleration Rate to brake the car (MADR). Cunto has used Vissim for safety simulation and concluded that the accident occurs when the DRAC value exceeds the MADR. This amount depends on many factors such as pavement conditions, car weight, and car braking system. Cunto and Saccomanno estimated the MADR value with a normal distribution, a mean of 8.45 m/s^2, and a standard deviation of 1.4, with a minimum value of 4.23 and a maximum of 12.68. In his study, the average of distribution (i.e., 8.45 m/s^2) was used as MADR.

AASHTO [42] recommends a 3.4 m/s^2 threshold for most drivers as the maximum deceleration limit. Also, Archer and Kungl [39] have shown that if the DRAC of a vehicle exceeds the MADR value of 3.35, the vehicle will be involved in a collision. Guido et al. [43] have considered this threshold value in their study to highlight vehicle interaction with more severe hazards and found that DRAC is a better indicator for showing the number and severity of vehicle interaction at risk.

(4) Other indirect measures: although three of the most common safety assessment indicators were investigated, some studies discuss other factors for indirect safety assessments. For example, Ozbay et al. [44] have proposed the MTTC index, which abandons the constant speed hypothesis during the collision period and considers vehicle acceleration. Bagdadi [45] introduced the jerk that represents the derivative of the acceleration as a suitable indicator for determining collisions, and Kuang et al. [46] presented a new index called ACI, which is a combination of the TTC, DRAC, and several other indicators used to evaluate the safety of freeways.

(5) Multiple indicators: in addition to studies that assess safety using only one measure, some studies use a variety of indicators.

Asljung et al. [47] examined the estimation of accidents with TTC and the Brake Threat Numbers (BTN), and determined the effect of these two indicators simultaneously with the use of extreme value theory on network safety. They predicted a model for evaluating the impact of AVs in the not-too-distant future. The BTN is an indicator that is calculated by dividing the DRAC by the MADR.

Zheng et al. [48] used the extreme value theory to predict future accidents. In this study, multiple indicators were used to assess safety. These indicators included TTC, PET/TTC, DRAC/PET, and DRAC, and they yielded almost more consistent results than a single measure. In this research, the potential conflicts that followed each of the relationships below were categorized.

$$\begin{aligned} R_{\mathrm{TTC,DRAC}} &= P\{\sim(\mathrm{TTC} > 0) \cup (\mathrm{DRAC} > \mathrm{MADR})\}, \\ R_{\mathrm{TTC,PET}} &= P\{\sim(\mathrm{TTC} > 0) \cup \sim(\mathrm{PET} > 0)\}, \\ R_{\mathrm{PET,DRAC}} &= P\{\sim(\mathrm{PET} > 0) \cup (\mathrm{DRAC} > \mathrm{MADR})\}. \end{aligned} \tag{7}$$

In the above relations, $R_{i,j}$ is the potential for an accident using the criteria i and j.

It can be gathered from previous studies that the use of multiple indicators would provide a better understanding of network safety. In this paper, we used TTC and DRAC indicators to assess the Potential Accident Number (PAN) which is equal to

$$\mathrm{PAN} = N_{\mathrm{TTC}=0} + N_{\mathrm{DRAC}>\mathrm{MADR}} - N_{(\mathrm{TTC}=0)\cap(\mathrm{DRAC}>\mathrm{MADR})}, \tag{8}$$

where N_i is the number of conflicts that satisfy the i condition.

It is not possible to determine a specific value for MADR. However, in this study, the recommended amount of AASHTO (3.4 m/s^2) was used to separate a possible accident from a nonserious conflict. Thus, it can be said that if the TTC is zero in the collision or the maximum deceleration is more than 3.4, an accident is probable. The reason for using the DRAC index alongside the TTC in this study is that a sudden braking rate can be a good indicator of driver inattention and distraction, which causes him/her to apply the brake hard.

For nonbasic scenarios, which include at least 10% of AVs, a fixed TTC value can no longer be considered for all vehicle types. Due to the rapid reaction of AVs to complex events, [7, 9] have stated that the amount of TTC for a collision between two AVs could be considered equal to one or even 0.75 seconds. However, this amount is still unknown and should be calibrated for real autonomous vehicles. In this study, 1 second was assumed for TTC in collisions between two AVs. For other collisions, i.e., two typical cars, or a typical car interacting with an AV, TTC was considered equal to the same value obtained from calibration.

4. Findings and Discussion

The total number of conflicts was screened according to the stated constraints. Also, the potential accident number was calculated from equation (8).

4.1. Comparing Two AV Projects for the Real-World Demand. In this section, we compare Coexist with the UK Autodrive project based on their ability to reduce total conflicts and PAN in the real-world condition. Tables 5 and 6 show the overall results for each intersection in both projects.

As can be observed in Table 5 and Figure 6, the UK Autodrive vehicles generally yield safer results for the Vesal intersection in terms of PAN reduction. Also, according to Table 5, UK Autodrive vehicles can better reduce total conflicts despite an exception in the 2040 scenario where the Coexist project leads to less total conflicts. The HV percent column in each table indicates what percentage of collisions occurs with conventional vehicles, and the rest of the accidents are between two AVs which can be caused by cyber threats and hacking due to their reliance on wireless communications, locations, and computing components [2, 21]. As can be seen in the 2045 scenario, although only 20% of cars are human-driven, still about 40% of conflicts for the Coexist project, and 45% for the UK Autodrive project, include conventional vehicles, which are relatively large numbers.

By performing a t-test to compare the current number of total conflicts with other scenarios, the Pvalue for all scenarios in both projects is less than 0.05. Therefore, it can be concluded that the presence of autonomous vehicles at the Vesal intersection, even with the least rate, can significantly contribute to the reduction of potential collisions at a 95% confidence level. The maximum total conflict reduction rate at this intersection with the full presence of AVs in the network is 56%, which seems to need further consideration.

Also, as can be observed in Table 6, both projects yield similar results for the Sattarkhan intersection. However, it can still be argued that, in general, the UK Autodrive project has a better safety performance for this intersection.

It is important to note that in 2030, although the number of total conflicts decreases, there is a slight increase in the number of crossing conflicts. In this scenario, regular cars play a role in almost all collisions (99.7%). As such, the reason behind this small increase in the number of crossing conflicts is the scanty acceptance of AVs and the lack of proper reactions to them by human-driven cars.

Figure 7 clearly shows that from 2035 to 2040, there is a sharp decline in the number of collisions, and the reason for this could be attributed to the diminishing role of human behavior and the noticeable increase in AVs in the network.

According to Table 6, in 2030, there will be no significant safety changes at the Sattarkhan-Niroo intersection because the P value obtained from the t-test for both projects in this scenario is more than 0.05. However, from 2035, the performance of this intersection will improve significantly with the arrival of AVs in the network. In 2050, the number of conflicts will decrease by more than 90% compared to the base state in both projects. This is a good indication that with a 100% AV penetration rate in the network, 90% of the accidents caused by human errors will disappear. Changes in the PAN are important from the start in the UK Autodrive project, but in the Coexist project, this importance begins in 2035. Thus, the hypothesis that the UK Autodrive project could further improve intersection safety is reinforced.

4.2. Comparing Various Total Demands. In this section, the three aforementioned scenarios for total demand are compared with each other for the UK Autodrive project in both intersections. Although this comparison should also be conducted for the Coexist project, it was preferred not to report these findings because the general trend of results for both AV projects is the same, and reporting all scenarios just leads to confusion.

PANs have been compared in Tables 7 and 8 for demand scenarios. As it can be observed, all alterations from real-world conditions to uncrowded scenarios are significant, but most changes are not important for overcrowded scenarios. The rationale behind this event stems from the fact that these intersections appear to be in a critical situation. Therefore, the circumstances cannot be worsened substantially. Besides, there is a slight decline in PAN for the last two scenarios of the overcrowded condition compared to their corresponding real-world scenario based on Table 7, which is far from the expectation. It is difficult to interpret the statistical significance of this finding, considering that it may be caused by variations between random seeds and the intrinsic stochasticity of microsimulation modeling. Nonetheless, it cannot be crucial because the P values for these scenarios are greater than 0.05. That is why such a change does not make any sense.

Table 5: Conflict results for Vesal intersection with the real-world demand.

Scenario	Total conflicts	Total reduction rate (%)	*P* value for total conflicts	Rear-end conflicts	Crossing conflicts	Lane change conflicts	PAN	PAN reduction rate (%)	*P* value for PAN	HV (%)
					Coexist project					
2020	465.9			141.6	237.4	86.9	285.8			
2030	431.0	7.5	0.0044	115.5	233.3	82.2	258.8	9.4	0.0128	99.4
2035	406.6	12.7	0.0336	103.3	224.3	79.0	234.9	17.8	0.0136	93
2040	324.9	30.3	0.0000	75.4	187.5	62.0	175.7	38.5	0.0000	64.3
2045	292.2	37.3	0.0002	77.5	165.7	49.0	149.1	47.8	0.0002	39.8
2050	214.3	54.0	0.0000	41.9	136.9	35.5	135.5	52.6	0.0395	
					UK Autodrive project					
2020	465.9			141.6	237.4	86.9	285.8			
2030	429.5	7.8	0.0009	113.1	236.2	80.1	250.4	12.4	0.0006	99.6
2035	387.9	16.7	0.0001	98.9	217.4	71.7	206.1	27.9	0.0000	93.8
2040	334.6	28.2	0.0000	85.1	187.6	61.9	166.9	41.6	0.0000	68.3
2045	273.7	41.3	0.0000	73.1	154.9	45.7	114.8	59.8	0.0000	45
2050	205.7	55.9	0.0000	44.5	127.2	34.0	114.1	60.1	0.8658	

Table 6: Conflict results for Sattarkhan intersection with the real-world demand.

Scenario	Total conflicts	Total reduction rate (%)	*P* value for total conflicts	Rear-end conflicts	Crossing conflicts	Lane change conflicts	PAN	PAN reduction rate (%)	*P* value for PAN	HV (%)
					Coexist project					
2020	2355.9			1568.6	445.0	342.3	1796.8			
2030	2255.8	4.3	0.343	1532.7	492.3	230.8	1636.9	8.9	0.160	99.7
2035	1664.3	29.4	0.000	1073.6	399.9	190.8	1187.3	33.9	0.000	97.3
2040	756.0	67.9	0.000	439.9	210.4	105.7	549.9	69.4	0.000	82.9
2045	395.1	83.2	0.000	217.7	122.8	54.6	298.3	83.4	0.000	64.7
2050	206.6	91.2	0.000	121.2	69.9	15.5	174.1	90.3	0.000	
					UK Autodrive project					
2020	2355.9			1568.6	445.0	342.3	1796.8			
2030	2225.1	5.6	0.065	1504.1	484.5	236.5	1618.4	9.9	0.018	99.7
2035	1540.6	34.6	0.000	969.0	390.0	181.6	1082.1	39.8	0.000	97.1
2040	684.3	71.0	0.000	388.9	201.5	93.9	489.5	72.8	0.000	83.3
2045	409.3	82.6	0.000	227.4	132.9	49.0	310.2	82.7	0.000	63.1
2050	157.5	93.3	0.000	87.3	65.2	5.0	138.3	92.3	0.000	

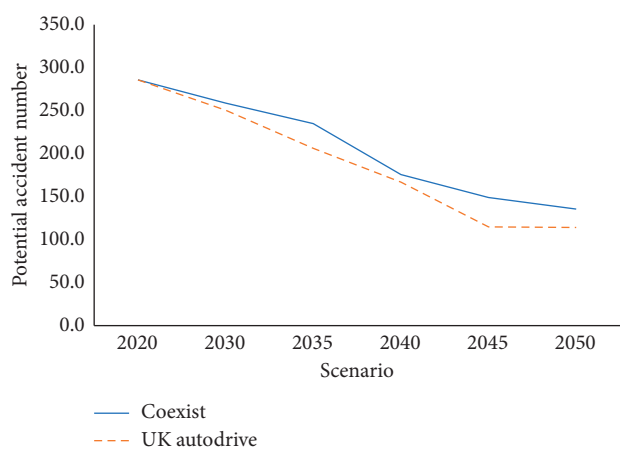

Figure 6: PAN comparison for two projects at the Vesal intersection.

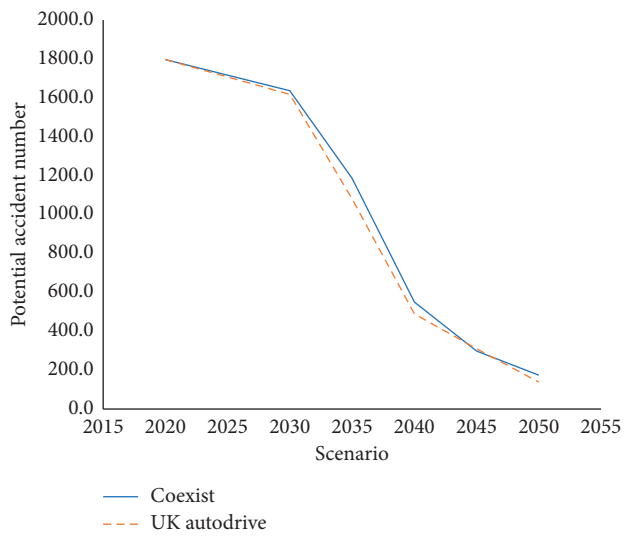

Figure 7: PAN comparison for two projects at the Sattarkhan intersection.

Table 7: The sensitivity analysis of potential accident number for each demand scenario compared to the real-world scenario at the Vesal intersection.

		Uncrowded			Overcrowded		
AV scenario	PAN for real-world	PAN	Change rate (%)	*P* value	PAN	Change rate (%)	*P* value
2020	285.8	76	−276	0.000	449.9	57	0.0006
2030	250.4	73.5	−241	0.000	286.4	14	0.102
2035	206.1	58.2	−254	0.0001	248.2	20	0.0209
2040	166.9	45.4	−268	0.0002	171.5	3	0.6548
2045	114.8	26.2	−338	0.001	113	−2	0.8549
2050	114.1	21	−443	0.0002	100.3	−12	0.1898

Table 8: The sensitivity analysis of potential accident number for each demand scenario compared to the real-world scenario at the Sattarkhan intersection.

		Uncrowded			Overcrowded		
AV scenario	PAN for real-world	PAN	Change rate (%)	*P* value	PAN	Change rate (%)	*P* value
2020	1796.8	411.5	−77	0.000	2062.1	15	0.2263
2030	1618.4	363.6	−78	0.0014	1878.4	16	0.7558
2035	1082.1	276.7	−74	0.0002	1460.9	35	0.0340
2040	489.5	142	−71	0.000	684.6	40	0.0622
2045	310.2	79.2	−74	0.000	375.3	21	0.2925
2050	138.3	21.6	−84	0.00015	148.5	7	0.6292

Figures 8(a) and 9(a) indicate that the reduction rate of potential accidents is ascending for both intersections in each demand scenario, as it would be anticipated. Moreover, these reduction rates have been further analyzed through *t*-tests in order to recognize the significance of these changes compared to their previous AV scenario. Results indicate that all changes are significant for each of the three demand scenarios in the Sattarkhan intersection (P value <0.05). However, alterations are not important for two cases of the uncrowded scenario at the Vesal intersection (2030 compared to 2020 and 2050 compared to 2045). This can be attributed to the fact that the potential accident number is relatively small at this intersection. So, the conditions cannot be improved considerably unless this intersection is equipped with some other facilities such as signalization.

The findings have further been investigated through presenting Figures 8(b) and 9(b). As it can be observed, crossing conflicts contribute to the majority of accidents at both intersections. This outcome is consistent with reality since there are many conflicting movements created by the vehicles from two opposing approaches at unsignalized intersections due to drivers' noncompliance with the defined priority rules. Lane change conflicts are infrequent in urban intersections, and they mostly happen on highways or freeways due to numerous lane-changing movements. Also, rear-end conflicts are common in signalized intersections.

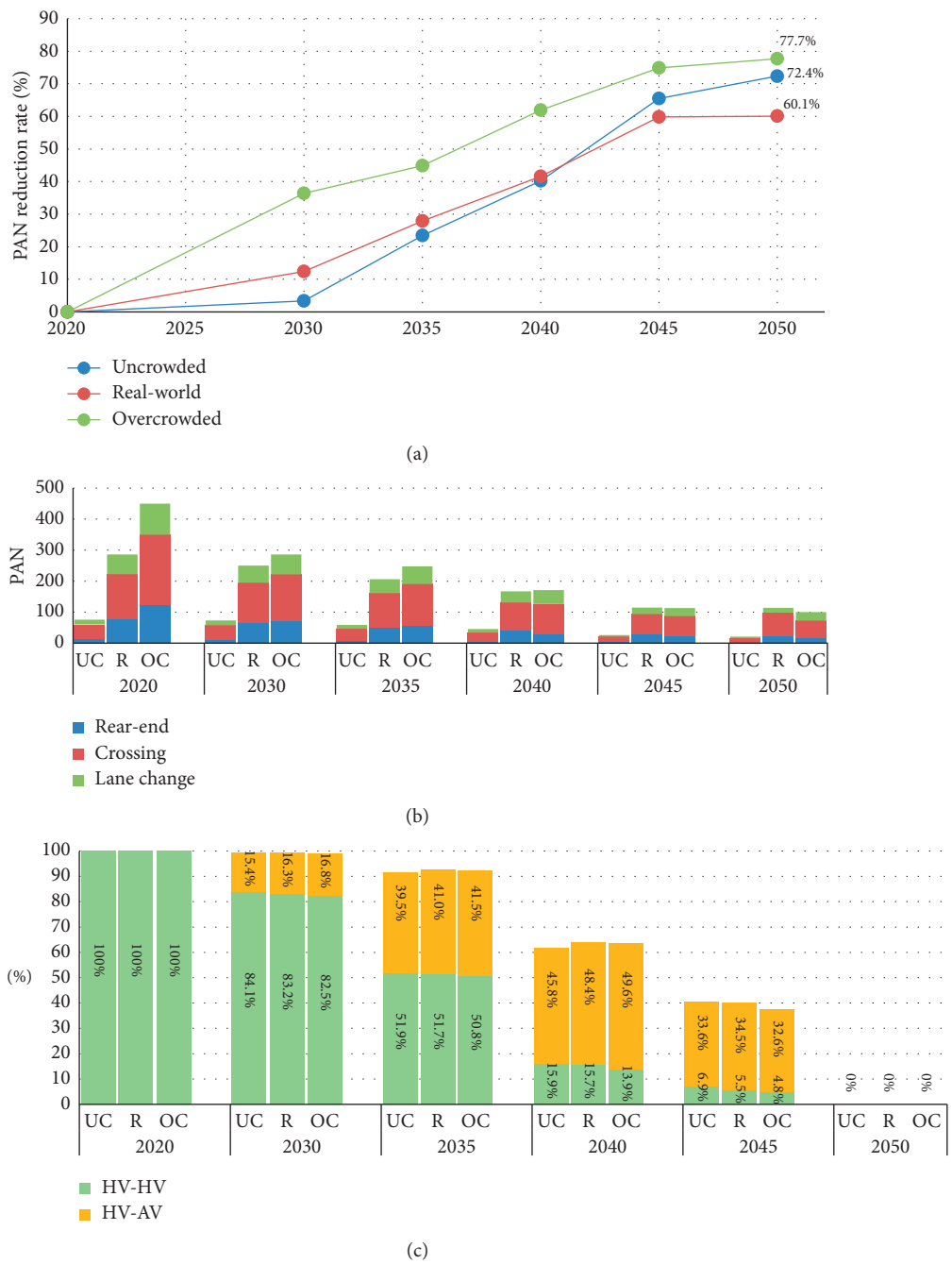

Figure 8: Detailed results of PAN at Vesal intersection for each demand scenario (UC: uncrowded, R: real-world, OC: overcrowded). (a) Potential accident number reduction rate. (b) PAN segregated by conflict type. (c) Percentage of PAN involving HVs.

This is mainly because of the existing "dilemma zone," which is the amber light period where drivers do not know whether they can pass the intersection safely or they should stop the vehicle.

The proportion of HVs involving in potential accidents has been shown in Figures 8(c) and 9(c). The rest of the accidents happen between two AVs, which is almost zero until 2035. The point that should be mentioned here is that these proportions are roughly constant between various demands for one specific AV scenario, and just the number of conflicts is altered for different total demands without any particular change in the proportion of conflict types.

Figure 9: Detailed results of PAN at Sattarkhan intersection for each demand scenario (UC: uncrowded, R: real-world, OC: overcrowded). (a) Potential accident number reduction rate. (b) PAN segregated by conflict type. (c) Percentage of PAN involving HVs.

5. Conclusion and Suggestions for Future Work

In this study, the effect of autonomous vehicles on the safety of two unsignalized intersections in Tehran was investigated, and the PTV Vissim software was used for simulation. Safety analysis and determining the number of possible conflicts was performed using the SSAM software. To model the driving behavior of conventional cars, distraction was calibrated for drivers using a driving simulator, in addition to the usual parameters. The distribution of distraction time and the angle of deviation were entered into the Vissim software. The Coexist and UK Autodrive projects were used to model the behavior of AVs and the scenarios for the market penetration rate of AVs were determined using Asadi's predictions [25]. Analyzing the results revealed that the advent of autonomous vehicles will lead to significant improvements in terms of safety at both intersections. Although the results of both projects are acceptable, in general, the UK Autodrive project performs better than Coexist at the intersections in question. The total reduction in collisions for

the Coexist project ranges between 7.5% and 54% for the Vesal Shirazi intersection and from 4% to 91% for the Sattarkhan intersection. In comparison, for the UK Autodrive project, these reductions are 7.8% to 56% and 5% to 93%, respectively. Also, two scenarios were defined for the total demand in addition to the base condition. Safety can be enhanced by increasing AVs in the network for both of these scenarios as well, and there is no incompatibility with the real-world condition.

One of the points to bear in mind is that the P value for the number of potential accidents at the Vesal Shirazi intersection in the last scenario for the UK Autodrive project is more than 0.05. Thus, significant changes could not be observed by the maximum presence of AVs compared to the previous scenario. In other words, it is not possible to reduce the number of possible collisions at the Vesal Shirazi intersection even by applying new restrictive measures. Therefore, it is recommended that this intersection be considered for changing to a signalized intersection according to warrant 7 of MUTCD [49] in future studies. The impact of this change on safety can then be assessed.

The indicator that was used to determine potential accidents in this research was a combination of DRAC and TTC. In later studies, other surrogate measures, such as PET or MTTC, could be considered.

In the scenarios described in this article, it was assumed that the demand in each case did not change compared to the previous one. Therefore, it has remained constant over the decades. However, for a more detailed study, it is better to determine the impact of AVs on demand changes and apply them to each scenario. Furthermore, different scenarios for this study had just various proportions of AVs or total demands. So, it is suggested to perform sensitivity analysis on other parameters such as the distribution of different types of AVs, the car following distance, and other related parameters.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that there are no conflicts of interest regarding the publication of this paper.

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