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Hong Yang
*Old Dominion University*, hyang@odu.edu

Zhenyu Wang
*Old Dominion University*

Kun Xie



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# Impact of connected vehicles on mitigating secondary crash risk

Hong Yang [a,*], Zhenyu Wang [a], Kun Xie [b]

[a] Department of Modeling, Simulation & Visualization Engineering, Old Dominion University, Norfolk, VA 23529, United States
[b] Department of Civil & Natural Resources Engineering, University of Canterbury, Christchurch, New Zealand

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A B S T R A C T

Reducing the risk of secondary crashes is a key goal for effective traffic incident management. However, only few countermeasures have been established in practices to achieve the goal. This is mainly due to the stochastic nature of both primary and secondary crashes. Given the emerging connected vehicle (CV) technologies, it is highly likely that CVs will soon be able to communicate with each other through the ad-hoc wireless vehicular network. Information sharing among vehicles is deemed to change traffic operations and allow motorists for more proactive actions. Motorists who receive safety messages can be motivated to approach queues and incident sites with more caution. As a result of the improved situational awareness, the risk of secondary crashes is expected to be reduced. To examine whether this expectation is achievable or not, this study aims to assess the impact of connectivity on the risk of secondary crashes. A simulation-based modeling framework that enables vehicle-to-vehicle communication module was developed. Since crashes cannot be directly simulated in micro-simulation, the use of surrogate safety measures was proposed to capture vehicular conflicts as a proxy for secondary crash risk upstream of a primary crash site. An experimental study was conducted based on the developed simulation modeling framework. The results show that the use of connected vehicles can be a viable way to reduce the risk of secondary crashes. Their impact is expected to change with an increasing market penetration of connected vehicles.


## 1. Introduction

Traffic crashes on highways not only induce delays, but also additional safety issues in terms of secondary crashes (SCs). The risk of having another crash in the presence of an earlier crash can be six times higher than the ones without an earlier crash (Tedesco et al., 1994). If the earlier crash presence on road for an additional minute, the likelihood of having a SC will increase by 2.8% (Owens et al., 2009). The occurrence of SCs further prevents incident responders from reaching crash sites timely and exposes road users to higher crash risk. In total, it was estimated that these SCs accounted for approximately 20% of all crashes and 18% of fatalities on US freeways (O'Laughlin et al., 2002; Owens et al., 2010). In addition, SCs contributed up to half of the congestion in urban area (Sarker et al., 2017). These crashes can result in millions of dollars of comprehensive

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* Corresponding author.
*E-mail addresses:* hyang@odu.edu (H. Yang), zwang002@odu.edu (Z. Wang), kun.xie@canterbury.ac.nz (K. Xie).

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costs associated with congestion, property damages, injuries, and/or fatalities (Pigman et al., 2011). Thus, reducing the risk of SCs is a critical concern for traffic incident management (TIM) agencies (Yang et al., 2013; Yang et al., 2014).

Despite the importance, there are still very few countermeasures that have been effectively deployed to reduce the number of SCs (Yang et al., 2013; Yang et al., 2014). In practices, many TIM agencies have adopted the quick clearance legislation and programs for preventing secondary crashes (Carson, 2008). However, due to the random nature and dynamic characteristics of crashes, it is often difficult to clear crashes in a short period of time in many actual circumstances. For example, it may take several hours to remove a serious crash in rural area involving a heavy truck carrying hazardous materials. Factors such as time of day, lanes closed, environment conditions, etc. also affect the clearance time (Nam and Mannering, 2000; Giuliano, 1989). Therefore, it is very challenging to implement any practical solutions targeting on SCs.

Given the emerging connected vehicle (CV) technologies, it is highly likely that many vehicles will soon be able to connect with each other through the vehicular ad-hoc networks. In particular, the U.S. Department of Transportation recently issued a proposed rule that would further accelerate the use of CV technologies throughout the U.S. light vehicle fleet. The rulemaking would enable vehicle-to-vehicle (V2V) communication technology on all new light-duty vehicles. The V2V communication enables information sharing and is envisioned to change the way of traffic operations. It will provide 360-degree situational awareness on road and all informed drivers can make better decision in response to abnormal conditions downstream and approach queues and incident sites with more caution. Thus, in case of crash conditions, the risk of secondary crash is also expected to be reduced. To examine whether such benefit is achievable or not, extensive evaluations of the innovative CV technologies are needed before widely deployed on road.

The main objective of this paper is to examine the safety benefits of deploying CVs for mitigating the risk of SCs. This allows us to investigate the feasibility of using CVs to reduce SCs and assess the magnitude of potential benefits under different market penetration rates. We intend to achieve the objective by developing a simulation-based framework for modeling the CV environment and analyzing the SC risk with an improved surrogate safety measure. The study findings will help design appropriate TIM strategies for preventing SCs with the application of CVs.

The remainder of the paper is organized as follows. The next section discusses up-to-date research focused on SCs. The third section presents the proposed methodology followed by the description of experimental study in the fourth section. The fifth section presents the test results and discussion. The final section concludes the paper with more perspective of this work.

## 2. Literature review

Existing studies on SCs mainly focused on three aspects, including (a) identification of SCs, (b) analysis of the characteristics of SCs, and (c) risk modeling of SCs.

First, a few studies have made efforts on developing specific approaches for identifying potential SCs given the occurrence of a primary crashes. For example, the static approaches have been introduced since 1990s (Raub, 1997a; Raub, 1997b). Such approaches require fixed spatial and temporal thresholds (e.g., one mile and crash clearance time + 15 min) to define the impact area of a primary crash. Any crashes occurred within the defined impact area of the primary crash will be classified as SCs (Raub, 1997b). Despite the variation of the spatiotemporal thresholds, many later studies adopted similar approaches to identify SCs (Latoski et al., 1999; Jalayer et al., 2015; Tian et al., 2016). Due to the subjectivity of defining the spatiotemporal thresholds, these static approaches have been questioned. This motivated tremendous efforts on developing a number of dynamic approaches such as queuing model-based approaches (Sun and Chilukuri, 2005; Zhan et al., 2009; Sun and Chilukuri, 2010; Zhang and Khattak, 2010), shockwave-based approaches (Zheng et al., 2014; Sarker et al., 2015; Wang et al., 2016), and data-driven approaches (Yang et al., 2013; Yang et al., 2014; Orfanou et al., 2011; Chung, 2013; Park and Haghani, 2016; Yang et al., 2017). Many of these approaches can largely improve the accuracy of the identification by dynamically updating the progression of the incident impact area. However, the need of additional datasets associated with incidents and/or traffic data from various sensors and computation resources remains a challenge for implementing them widely.

Second, with the support of various approaches for identifying SCs, many studies were able to successfully extract these special crashes and examine their characteristics specifically (Yang et al., 2013; Jalayer et al., 2015; Hirunyanitiwattana et al., 2006; Zhan et al., 2008; Carrick et al., 2015; Vlahogianni et al., 2010). For example, Zhan et al. (2008) examined the characteristics of SCs on freeways in Florida based on corridors, time, lane closures and incident types. Likewise, two studies (Hirunyanitiwattana et al., 2006; Kopitch et al., 2011) analyzed the characteristic of SCs for highways in California. With the improved identification algorithm, Yang et al. (2013) analyzed the SCs on the New Jersey Turnpike by mining the detailed incident records. Using Geographic Information System (GIS), Tian et al. (2016) filtered the SCs by three spatiotemporal criteria and investigate the SC frequency, types, severity, and contributing factors. These descriptive analyses revealed important characteristics of SCs, for example, the majority of SCs were found to be rear-end crashes. These information is valuable when developing countermeasures for preventing SCs.

Third, based on the identified SCs and their corresponding characteristics, a few studies have also statistically modeled the contributing factors that affect the risk of SCs. For example, logit models have been developed by several studies to examine the likelihood of SCs considering the features associated with primary crashes (Latoski et al., 1999; Zhan et al., 2009; Zhan et al., 2008; Kopitch et al., 2011; Karlaftis et al., 1999; Khattak et al., 2012). These models mainly focused on analyzing the impact of primary crash characteristics, environmental conditions, and geometric features on the risk of SCs. Key factors such as the duration of primary crashes, number of vehicles involved, crash time, lane closure, vehicle types, adverse weather conditions, etc. were frequently found to be related to the occurrence of SCs. With the availability of detailed traffic data, some study also incorporated real-time traffic information in the model (Xu et al., 2016). Considering the imbalance of primary crashes that induced SCs and the ones that did not, Yang et al. (2014) introduced the rare-event logistic regression model to predict the risk of SCs. Other than modeling the risk of SCs associated with individual primary crashes, some studies also developed models for predicting the frequency of SCs at the macroscopic level. For example, Khattak et al. (2010) developed Poisson, zero-inflated Poisson, and negative binomial regression models to estimate the frequency of SCs in Hampton Roads. Lately, Sarker et al. (2017) introduced the generalized ordered response probit model to predict SC frequency in the transportation network of Shelby County in Tennessee. Typical factors such as the roadway length, traffic volume, truck traffic, roadway location, etc. were found to affect the frequency of SCs. Despite these modeling efforts, there was still no consistent understanding of the causal relationship between SCs and potential contributing factors. This is largely attributed to the fact that each study relied on its own available datasets relevant to incidents, traffic, and/or environment. The lack of high-quality and standardized data and personal preference of model structures led to unavoidable bias and inadequate explanations in modeling results.

Overall, the aforementioned studies have contributed to literature by offering various approaches for determining SCs, revealing the unique characteristics of SCs, and quantifying potential contributing factors that affect the risk of SCs. However, very few studies have further taken advantages of the findings to explore feasible countermeasures that may help reduce the risk of SCs. As longer duration of primary incidents was found to raise the risk of SCs (Yang et al., 2014; Zhan et al., 2009; Khattak et al., 2009), optimized highway service patrols were considered to be an useful way to clear incidents and lower the chance of SCs (Latoski et al., 1999). For example, with the developed logistic regression models, Karlaftis et al. (1999) estimated that the potential benefit from SC reduction with the 1995 Hoosier Helper freeway service patrol program in Indiana was about $568,080. In addition, notifying road users in advance of unexpected traffic conditions downstream was also found to be helpful for avoiding secondary crashes (Kopitch et al., 2011). Kopitch et al. (2011) specifically evaluated the impact of changeable message signs (CMS) on secondary crashes and found that it was beneficial in terms of SC reduction. Despite the benefits, these countermeasures require additional investments in infrastructure projects or patrol resources, which largely limit their full-time implementation in large road networks.

With the emerging V2V communication technologies, CVs may soon offer a viable alternative to the countermeasures based on CMS or intensive highway patrol programs. This is because that approaching vehicles can easily access the advisory information on abnormal traffic conditions ahead and take actions accordingly. Thus, the present paper examines the potential benefits of using CVs as a feasible solution to reduce the risk of SCs.

## 3. Methodology

Primary crashes often disrupt traffic flow by induced queues. The presence of these queuing conditions causes significant safety concerns, particularly with the increased risk for crashes. As discussed earlier, most secondary crashes were confirmed to be rear-end crashes. If vehicles approach the back of a queue carefully, the risk of having secondary crashes is expected to be reduced. Thus, an effective countermeasure should be able to alert upcoming drivers in advance. CMS is a viable way to disseminate the downstream incident information to incoming drivers in advance. However, these variable message signs are often deployed at a limited number of locations due to the high costs of installation and maintenance. In addition, they are only visible to drivers within a limited range of distance. In case of severe weather conditions (e.g., rain and fog), their visibility will also be reduced. Meanwhile, vehicles driving on the section between two sparse distributed CMSs might not be timely informed in case of emergency. Therefore, an ideal solution should not be affected by the locations and weather conditions. Herein we introduce the CV application targeting on minimizing the safety impact of primary crashes by using V2V communications.

### 3.1. Conceptual design

Crashes are random incidents that may occur on roadways due to a set of issues related to human factors, traffic control, geometric conditions, and environment. Because of the capacity loss, traffic congestion can be a direct result of these incidents. The congestion is often accompanied by the waves of stop-and-go traffic that drivers are frequently complaining about. If drivers are distracted or inattentive in heavy traffic and fail to notice when the traffic comes to a stop or slow down, SCs may take place. These SCs can occur upstream of an initial crash. For example, Fig. 1 shows an example of a pair of primary and secondary crashes on a section of roadway. Other than the one shown in the figure, SCs may also occur in the opposite direction because of the rubbernecking phenomenon. In present study, we focus on the ones that occur in the same direction as the primary crashes. Nevertheless, the proposed approach is also applicable to SCs in the other direction.

Upon the occurrence of the primary crash *A*, the secondary crash *B* can be avoided if the involved vehicles can be notified in advance. However, such information is often delayed because of the necessary time for incident report, verification, information publish, and information acquisition. For example, in case of no surveillance cameras and/or instrumented sensors on road, the detection of the primary crashes can be delayed. The delayed dissemination of the incident information will extend

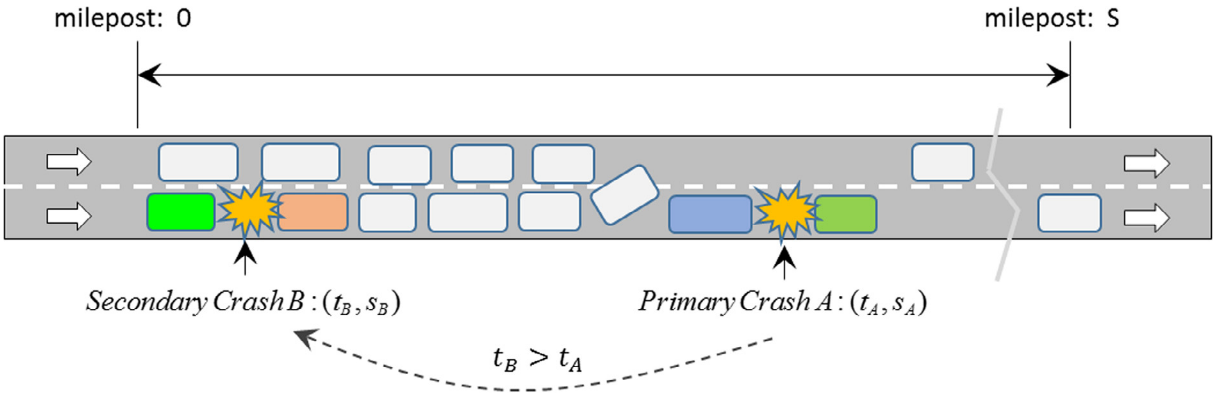


**Fig. 1.** An example of primary and secondary crashes.

traffic interruption by exposing many vehicles to an uninformed driving environment. On the other hand, if incident information is available to the incoming vehicles timely, it can assist them in incident preparedness and response proactively (e.g., using a detour route). The emerging V2V communication technologies offer such an opportunity that the incident information can be shared among the equipped vehicles in real time. The V2V communications can either disseminate local information in the vehicular ad-hoc network (VANET) or share information with the road side units (RSUs) linked to ground servers and traffic control centers. In this paper, we assume that the connected vehicles present in a network without any RSUs. Information can be exchanged only among CVs through the dedicated short range communications (DSRC). The DSRC systems have the on-board units (OBUs) with transceivers and transponders to receive and broadcast relevant information for each CV. In case of a primary crash, the CV near the incident site observing the crash will initiate and send the basic safety message (e.g., location of the crash) to the other CVs within its range of radio transmission. This paper assumes that DSRC radios can send and receive the safety messages 10 times per second over a transmission range of up to 1,000 meters. As shown in Fig. 2, the ones who received safety message may changes their behavior accordingly. For example, upon receiving the basic safety messages, these CVs can adjust their current driving status (e.g., change lane, increase headway, etc.) to maximize their safety benefit.

Despite the promotion of CVs, it is expected that vehicles without communication capability (e.g., white vehicles in Fig. 2) and CVs (e.g., blue vehicles in Fig. 2) will concurrently operate in mixed traffic environment over a relatively long period of time. Although CVs who received the safety message can optimize their driving behavior for safety, other non-equipped vehicles are still not aware of the crash condition. These non-equipped vehicles have to passively interact with each other as well as the informed CVs. They may adjust their car-following behavior and lane-changing behavior after perceiving and assessing the status of other surrounding vehicles. These induced interactions together with the adjusted behavior of CVs may change the overall safety performance of the traffic flow. However, quantitative facts are needed to assess the impact of CVs on safety.

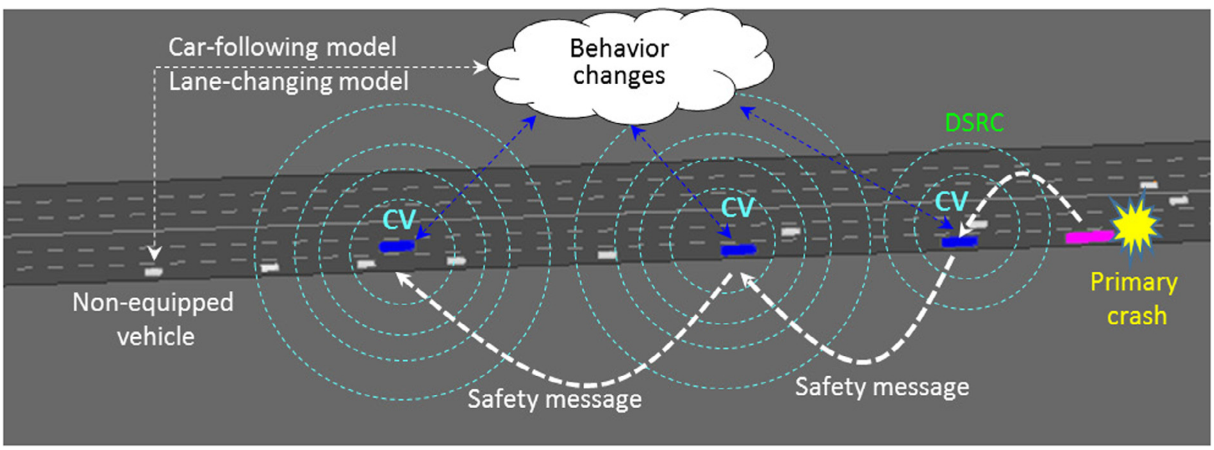


**Fig. 2.** Use of connected vehicles for reducing secondary crash risk.

### 3.2. Simulation and modeling framework

This study models CVs through the microscopic traffic simulation environment in Paramics. As mentioned earlier, the transmission range of each CV is assumed to be 1000 m. We also assume no communication latency and information loss. At each time step $t$, each subject connected vehicle $CV_t^i$ will scan surrounding CVs within its communication range. If there were $H_i(\geqslant 1)$ neighbors, denote each neighbor CV as $CV_t^{ih}$, where $h = 1, 2, \ldots, H_i$. These neighbor CVs will exchange information with the subject CV. If $H_i = 0$, no neighbor CV is found and no information exchange occurs. For example, 2nd CV was not within communication range of 1st vehicle at $t$ = 00:36:54 in Fig. 3(a). Thus, it did not receive the crash information initialized by 1st CV. Five seconds later, it was within the radius of the communication range of 1st CV and updated the crash information immediately at $t$ = 00:36:59 in Fig. 3 (b). Since the vehicles involved in a primary crash may not be a CV, the initial crash information is initiated by the CV next to the crash site. If the distance between this nearest CV and the crash site is greater than the transmission range, we assume no crash information will be collected and no safety message will be issued. In other word, the information collection and sharing will not occur until this nearest CV is within 1000 meters of the crash site (e.g., Fig. 3(a)). Under the crash condition, a CV that receives the safety message will change its behavior by adjusting driver awareness and aggression parameters in the simulation model. Driver aggressiveness controls the degree to which drivers respond to traffic flow conditions. A more aggressive driver will tend to drive faster and delay lane changes. The awareness parameter controls the degree of driver perception and collaboration with others on road, e.g., by changing headways to allow other vehicles to make lane changes. These parameters are denoted as integers in Paramics. In this study, we assume that a CV will update its aggressiveness parameter to one and awareness parameter to eight if the safety message was received. These assumed values are sufficient to distinguish CVs from other ordinary vehicles that have an average value of about four. For sensitivity analysis, one can certainly assign different values to these parameters to mimic the decisions of different drivers upon receiving the message.

The V2V communication mechanisms are modeled in Paramics through a customized application program interface (API) coded by a C plug-in. When a vehicle is generated in the simulation model, it will be randomly labeled as a non-equipped vehicle or a CV based on the user specified market penetration rate (MPR) for that simulation replication. A vehicle list is created to save the profiles of CVs in the network at current time step. When a CV is generated, its profile will be appended to the list. If a CV reaches its destination, it will be removed from the list and the list will be updated. Fig. 4 shows the proposed simulation framework. The simulation model provides us flexibility to define the length of each time step (e.g., 0.1 s, 0.2 s, 0.5 s, etc.). In this study, the time step is assumed to be 0.5 s to reduce the correlation of safety measures discussed in next section.

### 3.3. Measuring crash risk

In Paramics simulation model, we can create traffic incident to mimic the occurrence of a crash. However, it is not appropriate to subjectively create another crash that represents a secondary crash. Thus, the impact of CVs on the risk of secondary crash cannot be measured directly. As an alternative, this study assesses the risk secondary crash in terms of traffic conflicts. Existing studies have showed statistically significant correlation between frequency of traffic conflicts and collisions, for example, (El-Basyouny and Sayed, 2013; Gettman and Head, 2003). We adopted surrogate safety measures to capture traffic conflicts under different scenarios. As most secondary crashes were related to read-end collisions, a surrogate safety measure that can help describe the rear-end conflicts would be ideal. Thus, we used the time-to-conflict (TTC) to describe these linear conflicts. The concept of TTC describes the remained time that a subject vehicle will hit its leading vehicle if both vehicles' prevailing driving conditions do not change. Mathematically, it will be calculated based on the relative distance $d$ of two consecutive vehicles and their relative speed $\Delta V$.

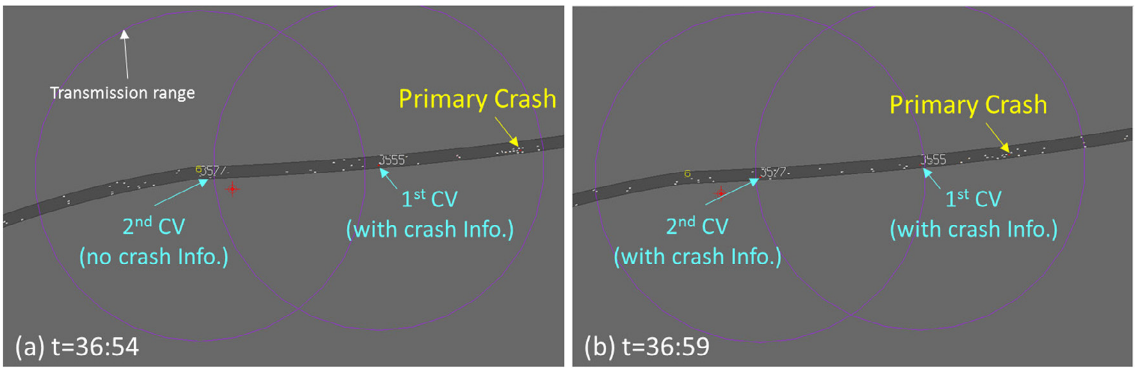


**Fig. 3.** Examples of information propagation.

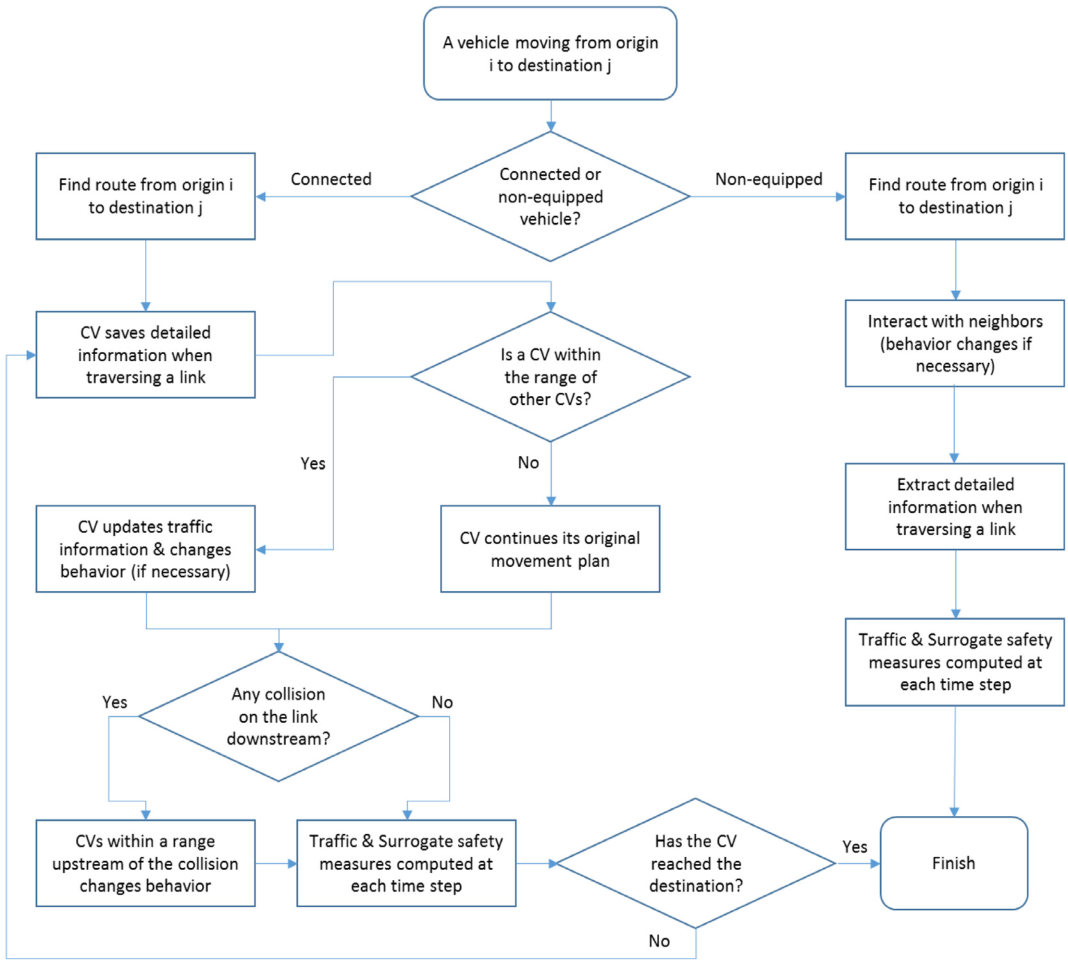


**Fig. 4.** CV modeling and simulation framework.

$$\mathrm{TTC} = d/\Delta V, \tag{1}$$

The Eq. (1) shows the conventional way to calculate the TTC indicator. The underneath assumption is that the current speed of the following vehicle must be greater than that of the leading one. If the current speed of the leading vehicle is faster, the surrogate safety measure cannot be calculated. However, this ignores the potential acceleration and/or deceleration maneuvers that these vehicles may implement. As an improvement, a modified procedure to calculate the surrogate safety measure was introduced in our early work (Ozbay et al., 2008). Thus, the modified procedure was applied in this study. The following equations briefly summarize the key components of the procedure.

$$V_F t_{FL} + \frac{1}{2} a_F t_{FL}^2 \geqslant D_{FL} + V_L t_{FL} + \frac{1}{2} a_L t_{FL}^2, \tag{2}$$

$$\frac{1}{2} \Delta a t_{FL}^2 + \Delta V t_{FL} - D_{FL} \geqslant 0, \tag{3}$$

where $V_F$ is speed of following vehicle, $V_L$ is speed of leading vehicle, $a_F$ is the acceleration of following vehicle, $a_L$ is acceleration of leading vehicle, $\Delta V$ is the relative speed such that $\Delta V = V_F - V_L$, $\Delta a$ is relative acceleration, $\Delta a = a_F - a_L$, $D_{FL}$ is initial relative distance, and $t_{FL}$ is time. Based on Eqs. (2) and (3), we can determine if there exists an minimum non-negative solution $t_{FL} = MTTC$ at each time step such that the following vehicle will collide with the leading one. *MTTC* denotes the modified TTC. If *MTTC* is relatively short, the time left for the following vehicle to change its driving status for avoiding the collision is limited. Thus, the likelihood of having a conflict is higher. Herein a predefined threshold $\mathrm{TTC}_{\min}$ is used to define the binary occurrence of a traffic conflict. If the calculated $MTTC \leqslant \mathrm{TTC}_{\min}$, then we label the occurrence of a conflict. Otherwise, no conflict will be labeled. Conventionally, a threshold value of $\mathrm{TTC}_{\min}$ between 1.5 s and 4 s have been frequently used in literature. In this paper, based on the consideration of the mean driver reaction time and information propagation delays, $TTC_{min}$ was assumed to be 1.5 s to determine critical conflicts. Then the number of these conflicts under different scenarios will be compared to quantify the impact of CVs on the secondary crash risk.

## 4. Experimental designs

The proposed simulation and modeling framework was tested in an experimental study. A 4-mile highway section that is similar to the east bound of the I-264 in Virginia Beach was modeled in Paramics, shown in Fig. 5. The modeled section has three lanes with a speed limit of 50 mph, which did not incorporate the original HOV lane in reality. Although actual traffic volume can be used, it did not provide flexibility to assess the proposed method under different traffic conditions. Alternatively, hypothesized hourly traffic demands of 2000, 3000, 3500, and 4000 veh/h were used to mimic different levels of traffic flow. No truck traffic was considered as the destination is a tourist attraction site. All simulated vehicles were randomly generated and had heterogeneous driving behavior determined by a number of parameters such as headway and reaction time. The default value of one second were used for headway and reaction time. We need to mention that these parameters can be tuned if the simulation model was applied to a real-world scenario. In this study, since no actual observations were available, the default values were considered. In order to mimic the primary crash, an incident was created to occur nearby the milepost of 2.4 at $t = 25$ min. Due to the incident, the middle lane was closed for 21 min. During the presence of lane closure, vehicles can still pass the crash site by using the left and right lanes with a maximum allowable passing speed of 5 mph. When $t = 46$ min, the incident was cleared and all lanes were open to traffic normally. The total simulation time is $t = 75$ min and the initial 15 min were considered as the simulation warm-up period. Traffic conflicts based on the proposed surrogate safety measure in each scenario were collected for one hour after excluding the warm-up period.

The aforementioned experimental design offers an ideal controlled simulation environment to investigate the impact of CVs on secondary crash risk. It is envisioned that the deployment of CVs will gradually increase. Thus, we have considered the market penetration rates of CVs changing from 0 to 25%, with an increment of five percent for each scenario. Considering the levels of demand and MPR, we have to test$4 \times 6 = 24$scenarios in total. In order to determine the minimum number of simulation runs for each scenario, a sequential procedure was used. This procedure helps obtain an estimate of the simulated frequency of conflicts with a relative error of $\gamma(0 < \gamma < 1)$ and a confidence level of $100(1-\alpha)$ percent. The procedure starts with $n$ pilot runs with different random seeds, and compute the half-length $\delta$ of the confidence interval as follows:

$$\delta = t_{n-1,1-\alpha/2}\sqrt{S^2(n)/n}, \tag{4}$$

where $t_{n-1,1-\alpha/2}$is the critical value at $1-\alpha/2$ of the $t-distribution$ with $n-1$ degree of freedom and $S^2(n)$is the sample variance of the simulation results. If $\delta/|\bar{X}(n)| \leqslant \gamma$, $\bar{X}(n)$will be considered as the point estimate for the simulation results in a given scenario and no additional simulation runs will be implemented. $[\bar{X}(n)-\delta, \bar{X}(n)+\delta]$ will be an approximate $100(1-\alpha)$ percent confidence interval for the simulation results. Otherwise, if $\delta/|\bar{X}(n)| > \gamma$, replace $n$ by $n+1$ and make a new run of the simulation with a different random seed and update $\delta$ and $\bar{X}(n)$ for comparison. In this study, we considered a relative error of $\gamma = 0.2$ and a minimum of $n = 15$ for running the simulation experiments for each scenario. In total, at least $24 \times 15 = 360$ simulation runs are needed for the 24 scenarios. To avoid manual adjustment of the simulation configuration file, we have developed a batch script with the assistance of an external program developed in *R*, an open-source software for statistical analysis. The batch script enables us running all replications of a scenario automatically. Computationally, each scenario only took 40–140 s (depending on the demand and MPR) to complete the required simulation tests on the Windows 7 platform.

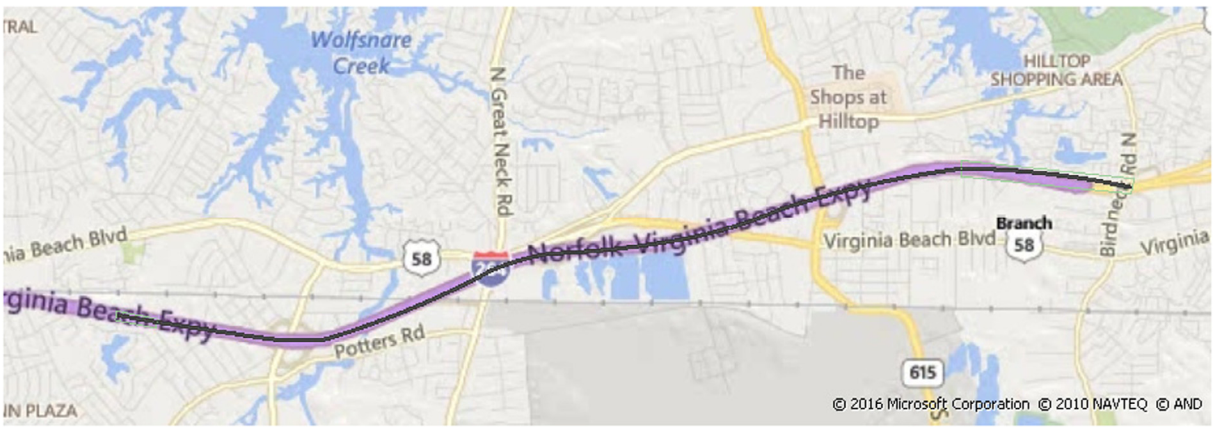


**Fig. 5.** Simulated highway section between interchanges 19A to 21B of I-264 in east bound.

## 5. Results and discussion

For assessing the risk of secondary crashes, the *MTTC* measures were computed for each simulation scenario and the traffic conflicts identified by the short *MTTC* were recorded in a .csv file in each simulation run. A *R* program was developed to analyze all experimental results.

Fig. 6 shows the simulated conflicts under each scenario. For any given level of MPR, the number of traffic conflicts increased as the traffic volume increased. This is consistent with findings in literature that there is positive correlation between conflicts and traffic volume (El-Basyouny and Sayed, 2013). When the MPR increased, the number of traffic conflicts decreased if the volume was relatively high (e.g., 4000 veh/h). For example, the average number of conflicts was reduced by more than 30% when MPR was increased from zero percent to a quarter given the volume of 3500–4000 veh/h. Even with 5% of CVs, the conflict frequency was reduced by about 10% when volume was 3500–4000 veh/h. However, when the volume was relatively low (e.g., 2000 veh/h), the number of conflicts did not change too much. Of the same level of demand, the standard deviation of the conflict frequency did not show a clear pattern. This should be attributed to the random nature when generating the CVs in simulation. The arrival pattern of the CVs will affect the simulated conflicts.

Table 1 presents the statistical comparisons of the simulated conflicts between scenarios with and without connected vehicles. The results suggest that the benefits of using CVs to reduce the risk of secondary crash were not always notable if the volume was 2000 veh/h. Increasing the MPR from zero up to 25% still did not significantly reduce the number of conflicts. When the volume was 3000 veh/h, no significant benefits were obtained with a MPR of 5–15%. However, if the MPR was further increased, we can see that the number of conflicts was significant reduced, with an estimate of approximately 200. If the volume was 3500 veh/h or more, even a small proportion of CVs can significantly reduce the conflict frequency.

Fig. 7 illustrates the spatiotemporal impact of different levels of CVs on the simulated conflicts. Although the simulation time for each scenario was 75 min, each figure only presents the results that excluded the first 15 min warm-up period. From Fig. 7, the increase in the MPR of CVs notably changed the conflicts associated with the induced queue by the primary crash. For the periods and locations (dark-green area in the figures) that the impact of the primary crash did not reach, the frequency of conflicts was consistently low. When there was no CV, many conflicts (highlighted by yellow, orange and red colors in the figures) were observed within the queue. When the MPR of CVs increased, the conflicts were less dense within the queue. Similar patterns were observed for scenarios with other high levels of volume.

Fig. 8 shows a comparison of the spatiotemporal distribution of conflicts under different volume conditions with a fixed MPR. As volume increased, conflicts were observed further upstream of the crash site. This was consistent with the growth of the queue. When the volume was 2000 veh/h, the closure of the middle lane did not induce heavy congestion and only a few conflicts were observed near the location of the primary crash (see Fig. 8(d)). The availability of the left and right lanes can still serve the incoming vehicles. However, when the volume was increased, the available throughput capacity was far less than the arrival rate, which resulted in a fast growing queue. In the queuing process, vehicles that initially traveled in the middle lane would seek opportunities to change lanes. In addition, the dynamic progression of the queue would also cause more stop-and-go traffic. Together more induced vehicle interactions led to more conflicts when traffic became dense.

Overall, the simulation results suggest that the deployment of CVs has the potential to help reduce the risk of secondary crashes measured by traffic conflicts. However, the benefit was not always achievable, especially when the volume was relatively low. This should be attributed to the fact that a low volume reflects a low-density condition that allows most vehicles to have relatively long (time and space) headways. The deployed CVs changing their behavior in such a condition cannot

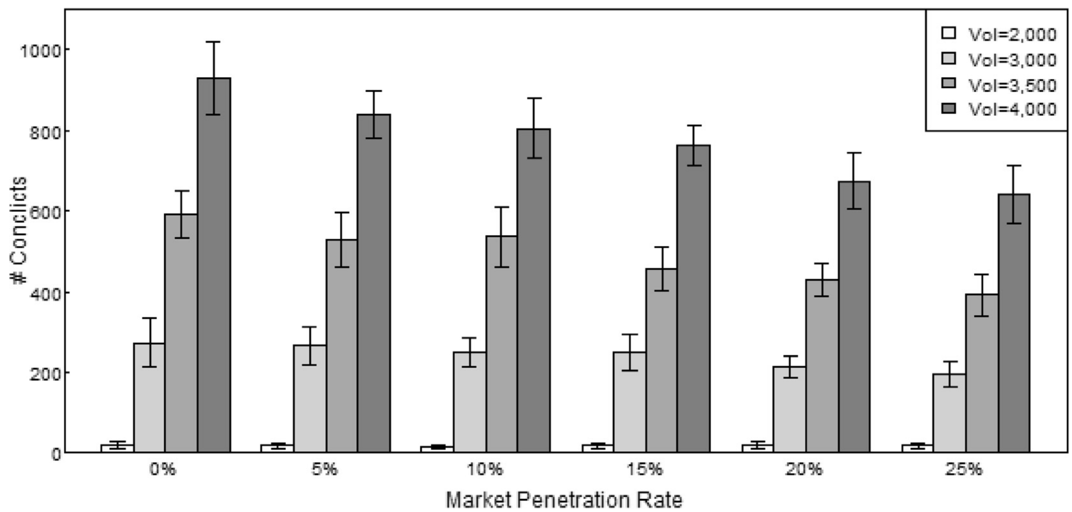


**Fig. 6.** Impact of CVs under different traffic conditions and MPRs.

**Table 1**
Welch's two sample *t*-test results (decimal #: *p*-value).

| Volume | MPR = 5% | MPR = 10% | MPR = 15% | MPR = 20% | MPR = 25% |
|---|---|---|---|---|---|
| 2000 | 0.4966 | 0.0581 | 0.3134 | 0.4911 | 0.2916 |
| 3000 | 0.7165 | 0.2344 | 0.2102 | 0.0030** | 0.0003** |
| 3500 | 0.0108** | 0.0290** | <0.0001** | <0.0001** | <0.0001** |
| 4000 | 0.0029** | 0.0003** | <0.0001** | <0.0001** | <0.0001** |

** Significantly different from MPR = 0% at the level of significance $\alpha = 0.05$.

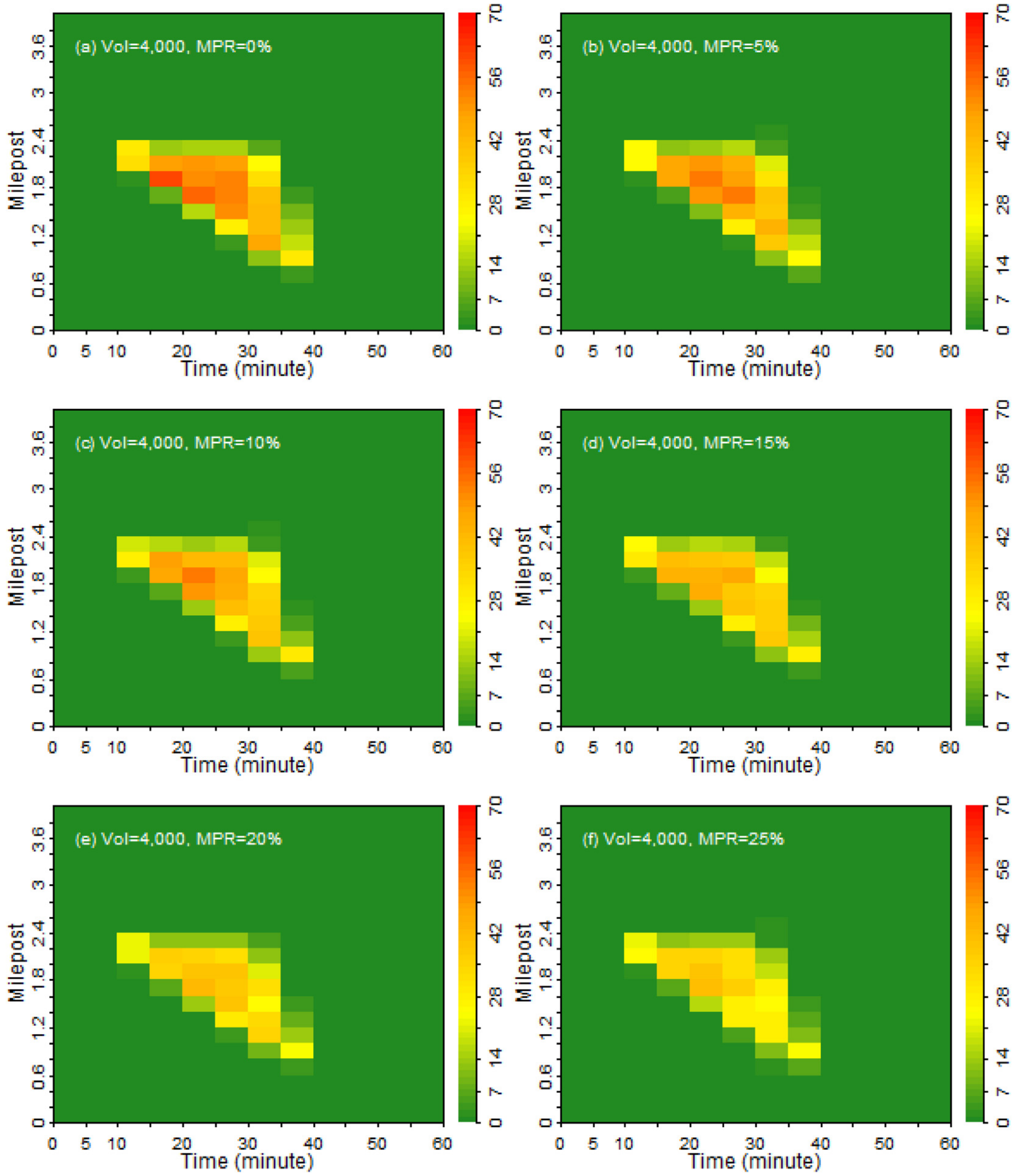


**Fig. 7.** Spatiotemporal distribution of conflicts under different MPRs.

immediately affect their sparse distributed neighbors. When other vehicles perceive the changed behavior of CVs, they have more time and space to take safer actions accordingly. However, when traffic becomes denser, each vehicle will have less freedom because of the short headways. Each CV acts as a regulator such that their behavior change will quickly affect

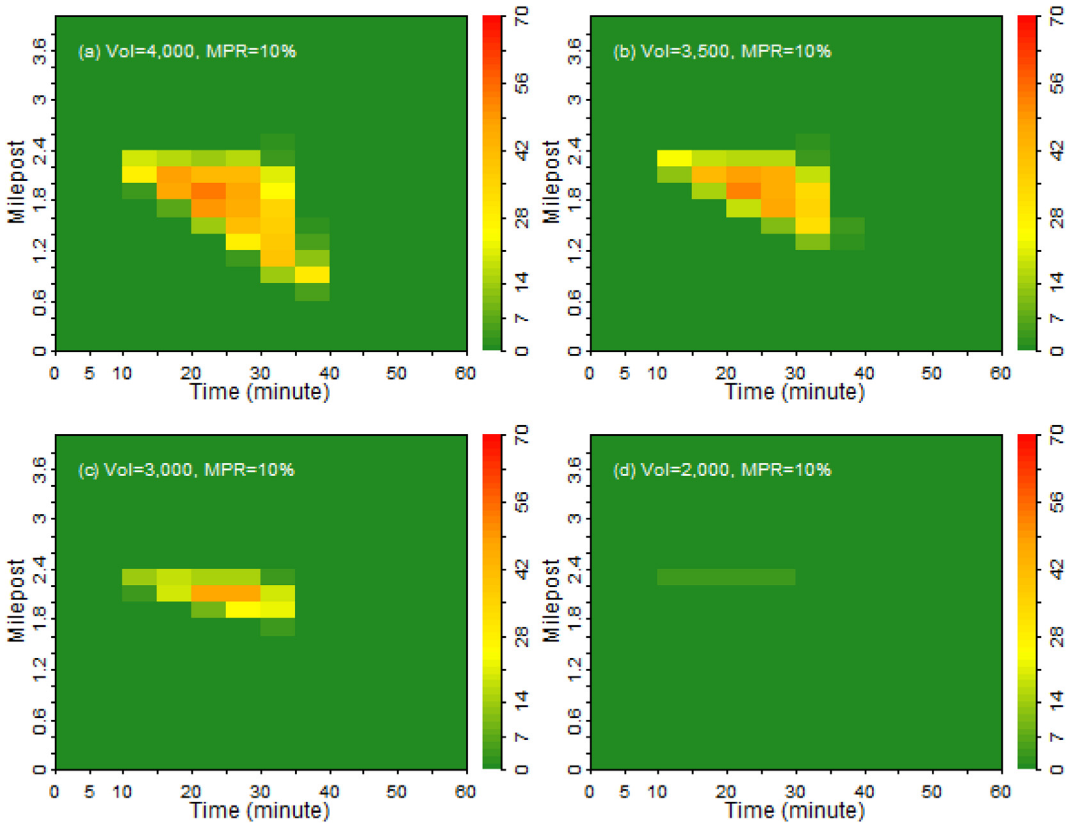


**Fig. 8.** Spatiotemporal distribution of conflicts under different traffic conditions.

the other neighbors. The information exchange is more likely to occur when there are more CVs forming a communicable fleet in the flow. Thus, the role of a regulator is more likely to be propagated to other CVs upstream, and therefore affect other vehicles far away from the crash site.

## 6. Conclusions

This study established a microscopic simulation and modeling framework to assess the impact of vehicle connectivity on the risk of secondary crashes. The V2V communication module of connected vehicles was developed using the API in Paramics. An improved surrogate safety measure, namely *MTTC*, was considered as the more appropriate indicator to quantify the safety performance for a number of scenarios with and without CVs. Based on the findings of the experimental study on the proposed simulation and modeling framework, it is concluded that the deployment of CVs can greatly reduce the risk of secondary crashes if they were deployed reasonably. The risk of secondary crashes can be significantly reduced by about one third if the MPR reaches a quarter under a high-volume condition. If the traffic is dense, the use of a small proportion (e.g., 5%) of connected vehicles will successfully reduce the risk of secondary crashes by about 10%. However, the benefit of CVs would not be notable under low-volume conditions. This is because that only very few spare distributed CVs under low-volume conditions can communicate with each and affect a limited number of vehicles by their changing behavior. Moreover, the initial crash information collected by a CV is likely to be delayed if the MPR is low and the number of CVs is small. It would be interesting to further study whether the deployment of RSUs in addition to CVs under low-volume conditions would help reduce the risk of SCs.

It is necessary to mention a few limitations related to the proposed simulation and modeling framework. First, despite the computational efficiency, the proposed vehicle communication module was simplified. We have not specifically modeled the impact of the information propagation delays on the simulation results. It is expected that the simulated conflicts will be slightly changed because CVs will be further exposed to potential conflict risk due to delayed information. For more realistic communication simulation, it would be helpful to integrate other advanced network simulators (e.g., NS-2) with the microsimulation model. Second, we have assumed that all CVs maintained the same level of awareness and aggressiveness after receiving safety messages. To test different compliance rates and heterogeneity of drivers, one can allocate different levels of awareness and aggressiveness for each CVs. Since drivers may need additional time to interpret the received information, their delayed responses should be carefully considered. In addition, modified car-following and lane-changing models that describe more realistic behavior changes of CVs should be considered. Finally, the study was based on a hypothesized highway section. More tests on other types of networks (e.g., two-lane highways; networks with alternative routes, etc.) are suggested.

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