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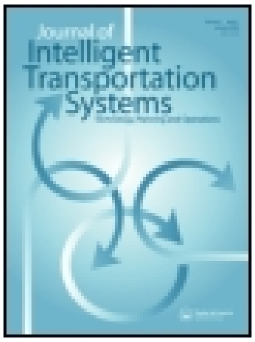

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Evaluating connected vehicle-based weather responsive management strategies using weather-sensitive microscopic simulation

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ABSTRACT

The purpose of this study is to perform analysis, modeling, and simulation (AMS) to investigate the effectiveness of connected vehicle (CV)-based Weather Responsive Management Strategies (WRMS) to address safety concerns on freeway corridors under adverse weather conditions. This study investigates three CV-based WRMS applications: Forward Collision Warning (FCW), Early Lane Change (ELC) advisory, and Variable Speed Limit (VSL), designs operational alternatives for WRMS using CV data, and develops an AMS tool using a weather-sensitive microscopic traffic simulator to understand the effectiveness of the three WRMS under different scenarios. Various CV market penetration rates (MPR), weather conditions, and WRMS algorithm settings are tested in this study. The case study is based on a real-world freeway corridor, a segment of the I–80 Connected Vehicle Testbed in Wyoming. The simulation results show the effectiveness of selected WRMS applications and provide operational insights that state and local transportation agencies may use in future strategic planning and operations of their weather-responsive programs.

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Analysis; connected vehicles (CV); early lane change; forward collision warning; modeling; and simulation (AMS); variable speed limit; weather responsive management strategies (WRMS)

Introduction

Weather affects roadway safety through increased crash risk, as well as exposure to weather-related hazards. Road-weather-related crashes place a substantial financial burden on society, with an average loss of $22 billion annually in the U.S. in travel delays, fatalities and injuries, productivity loss, insurance, and emergency services costs (Pisano, 2008). These are also expected to rise to $51 billion annually in the U.S., including unreported crashes (Pisano, 2008). The economic effects of road weather events are significant due to the reduction of overall surface transportation performance. Crash frequencies increase significantly during inclement road weather conditions (Eisenberg & Warner, 2005), although traffic demand is far lower than in normal conditions. As safety has been considered the primary objective of traffic operations, understanding the influence of road weather events on both the frequency and severity of crashes is vital.

With the advancement in wireless communications, it is now possible to connect vehicles to enable them to communicate and cooperate. In this context of smart vehicles and the Internet of things (IoT), Connected Vehicle (CV) technologies are playing a major role in unleashing the true potential for connected vehicles to collect and disseminate pertinent data among each other for the sake of better decision making and enhanced safety. The term CV is used to broadly designate any smart vehicle with wireless connectivity to the Internet, local network (or the Cloud), other vehicles on the road (V2V), personal communication devices, roadside infrastructure (V2I), or control centers.

CV safety applications are being designed to increase situational awareness and reduce or eliminate crashes through vehicle-to-infrastructure (V2I) and vehicle-to-vehicle (V2V) data transmissions. These V2V and V2I applications support advisories, warnings, and vehicle and/or infrastructure controls. From a government perspective, the impetus for deploying CV technologies is to deliver applications with a road safety focus that will reduce the number of fatalities and serious injuries. Among various CV applications, Forward Collision Warning (FCW), Early Lane

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Change (ELC) advisory, and CV-based Variable Speed Limit (CV-VSL) are regarded as three effective means to improve safety, mobility, and sustainability of the system. These applications can be packaged into the CV-based traveler information messages (TIMs) and be part of the V2V and V2I communication using the dedicated short-range communications (DSRC) technology (Miao et al., 2012).

Adopting WRMS that uses road weather data from Integrating Mobile Observations (IMO) and CV technologies will enable State and local agencies to be proactive in managing the system before negative impacts occur (Kitchener et al., 2017). Additionally, more accurate and location-specific road weather condition data will allow appropriate traffic management strategies to be deployed where they are needed and reduce the costs associated with winter maintenance. However, agencies face challenges in adopting and implementing CV-enabled WRMS, as there are many unknowns and uncertainties associated with implementation. Agencies need to know how WRMS can be enhanced with CV data, how many or what percentage of vehicle fleets need to be equipped with road weather sensors and vehicle-based technologies or should be receiving mobile data from other sources, how CV-enabled weather-responsive traffic and maintenance strategies will improve the performance of the transportation system, and what tools are available to help evaluate or make decisions on CV-enabled road weather management strategies. These questions can be answered by reviewing and applying appropriate tools that can determine, by looking at the resulting performance of the highway system, how and to what extent CV data should be used for specific road weather management strategies under various road weather, traffic, and operational conditions.

Research objectives

This study aims to develop a weather-sensitive AMS (analysis, modeling, and simulation) tool to investigate the effectiveness of WRMS for addressing existing transportation safety problems under adverse weather conditions. The developed AMS tool is evaluated in a case study that involves simulation on the I-80 corridor, as a part of the Wyoming CV testbed, and investigates the effectiveness of CV deployment in enabling better WRMS. Then we applied the AMS tool under multiple scenarios to simulate, evaluate, and discuss the effectiveness of three WRMS, ELC, FCW, and CV–VSL.

The remaining of this article includes the review of the state-of-the-art of WRMS, the introduction of the methodology which contains detailed information of the development of the AMS tool and selected CV-based WRMS applications, the background information of the case study, the simulation framework and network calibration, the simulation result analysis to demonstrate the potential impacts of WRMS under different weather scenarios, and finally, the recommendations of future studies including simulation limitations, unanswered questions, and suggestions.

Literature review

Weather-responsive management strategies

WRMS is a key initiative under the FHWA's Road Weather Management Program. The WRMS initiative supports transportation agencies and professionals in developing better advisory, control, and treatment strategies that mitigate mobility and safety challenges due to adverse weather (Gopalakrishna et al., 1999). It has enabled innovative and award-winning practices like citizen reporting systems, weather-responsive traveler information, and weather-responsive active traffic management. During adverse road weather, deterioration in driving conditions reduces safe driving speeds substantially, and most drivers do not recognize those hazards, which exaggerate the crash risk (Edwards, 1999). Since the initiation of technology in transportation, intelligent transportation system, such as connected vehicles, has been a key element in minimizing adverse road weather impacts to traffic operations (Agarwal et al., 2005; Zhang et al., 2004). Traffic managers can implement a myriad of traffic operation strategies, including winter maintenance programs, and provide traveler information via V2I communication, which is also of use in regular traffic operations (Cools et al., 2010). On-site interviews by Kilpelainen and Summala found that travelers who accessed road weather information were most likely to adjust their trip planning to avoid severely affected routes. However, travelers perceived actual driving conditions were better than forecast in daylight and were worse at night (Kilpeläinen & Summala, 2007).

CV based traveler information messages

Real-time traffic information systems, for instance, traveler information messages (TIM), or variable message signs (VMS), are considered as an efficient method to convey messages to drivers with traffic information and upcoming incidents. This method could be embedded in autonomous/CVs (Genders & Razavi, 2016) where CVs provide continuous real-time information sources about their speed and location to estimate the traffic conditions at random locations (Grumert & Tapani, 2020). Sui and Young (2014) developed a linear regression model to identify the impacts of VMS on driver speed behavior under different adverse weather conditions using field data. Modeling results indicated that TIMs were effective at reducing drivers' speeds along rural freeway corridors from 5 mph to 20 mph. Zavareh et al. (2017) investigated the effects of displaying safety messages that contain risk level information on driving behavior based on traffic flow data collected from loop detectors. A comparison between the control group and experimental group revealed that the effects of high-risk messages were consistently related to safe adaptations; while the effects of messaging on rear-end conflicts were significant only in the fast lane at night time. Wu et al. (2018) assessed the effectiveness of real-time fog warning systems by quantifying drivers' speed adjustments under different roadway types, traffic conditions, and fog levels. The results suggested that TIM was beneficial to speed reduction before entering the fog area.

CV based variable speed limit

The potential to provide essential data at the microscopic level of CVs can also improve the application of VSL. Khondaker and Kattan (2015) built a multi-objective optimization function in a VSL control algorithm among mobility, safety, and sustainability. The result revealed that optimizing for safety alone is sufficient to achieve simultaneous and optimum improvements in all measures under high CV market penetration. Yang et al. (2019) developed a driving simulator testbed to assess the impact of Wyoming's CV-based VSL (CV-VSL) application on truck drivers' behavior under adverse weather conditions. Traffic flows utilizing CV-VSL technology tended to exhibit lower average speeds and speed variances compared with baseline scenarios, therefore improving safety. Han et al. (2017) showed the CV-based VSL strategies can effectively impose dynamic control over continuous time and space, enabling faster queue clearance around a bottleneck, less restrictive control with higher control speed, and simpler control via only one or a small number of CVs comparing with Variable Message Sign (VMS)-only VSL strategies. Wu et al. (2020) developed a VSL control algorithm with consideration of the different relationships between the gap and visibility distance. The VSL strategy was also tested in the fully (CV) environment. A feedback control framework was developed to combine the VSL and CV control. The proposed VSL strategy was implemented and tested for a freeway section with a bottleneck through the micro-simulation software VISSIM and the intelligent driver model (IDM) was employed to account for car following in the CV environment. The results demonstrated that the VSL control played an important role in reducing rear-end crash risk and the effects of the VSL control could be affected by compliance rates.

Knowledge gaps and challenges

The above trends clearly show that there is an existing gap in comprehensively understanding the safety performance of CVs in mitigating the risk of crashes on highways under adverse weather conditions. There are a limited number of simulation studies and no field deployments to understand weather responsive CV strategies. Therefore, in this article, we aim to address this gap and tackle scenarios under poor visibility and pavement conditions due to adverse weather conditions, and explore how we can apply cooperative CV applications to enhance driver's situational awareness and mitigate crashes. In fact, poor visibility and pavement conditions due to fog, heavy rain, or snow not only impact the driving conditions but also alter the driving behavior of motorists who are often not well trained to cope with poor driving conditions. Therefore, this study also aims to exploit V2V communications to proactively warn drivers to avoid cascaded collisions. Additionally, this study also serves as a feasibility study for a real-world CV deployment site in Wyoming, one of the three connected vehicle testbeds in the U.S.

Methodology

Analysis, modeling, and simulation (AMS) implementation

Analysis platform development

This article focuses on safety analysis and the effectiveness of the WRMS in reducing crashes or safety risks. The evaluation of safety risks requires detailed individual vehicle space-time trajectories at the sub-second level, which can only be generated through microscopic simulation tools. Therefore, the research team considers the microscopic models and simulation tools as the optimal option for the safety analysis

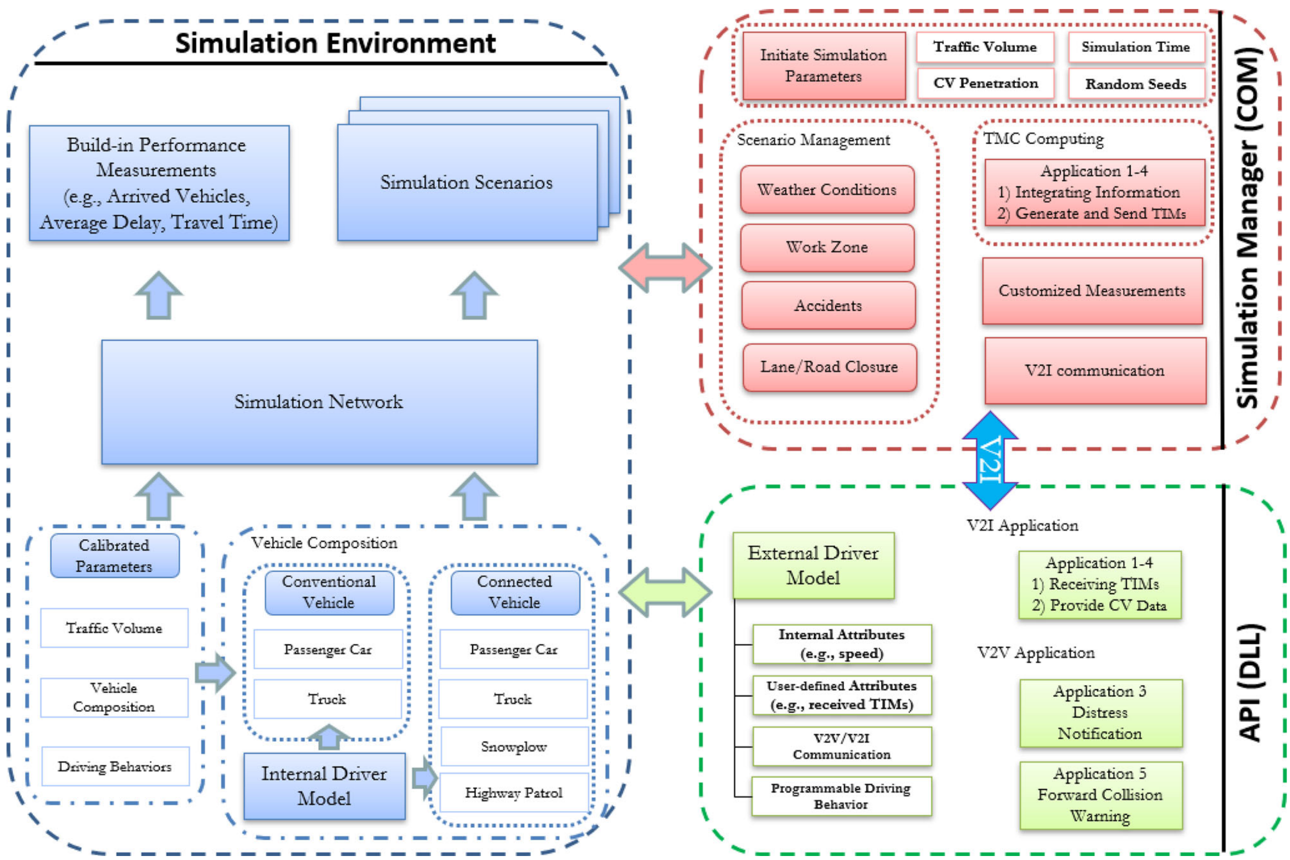

Figure 1. Detailed simulation framework of the simulation network, component object model, and application programming interface.

in this study. The microscopic simulator VISSIM is the one used for this study (PTV, 2018).

To implement various CV applications, three major modules and an optional extension are needed in the AMS tool: the simulation network module, the simulation manager module, and the application programming interface (API) module. The detailed overall simulation framework of this study is shown in Figure 1.

The simulation network is the underlying transportation network that will be used for testing a large variety of CV algorithms. In this study, various VISSIM networks are created for different calibrated weather conditions (i.e., types of driver behavior). The simulation manager is enabled through a component object model (COM) interface to support easy scenario building and system-level control. The Simulation Manager allows users to easily adjust control parameter values crucial for the implementation of CV. It also provides users with an interface to conveniently modify simulation scenario parameters, such as market penetration rates (MPR), traffic volumes, and simulation times. The Simulation Manager can be used to realize online or off-line implementations of the AMS tool. The API module is a program that determines driving behavior by customized programs for corresponding parameters in different CV applications. This feature allows the user to model (and test) various CV applications by substituting the built-in driving behavior with a fully user-defined behavior for vehicles.

Mapping between weather conditions and driver models

Microscopic simulations cannot directly accept weather and road (i.e., pavement) condition inputs. In this study, weather and road conditions are reflected using different driver behavioral models through the parameters such as look-ahead distance, desired following gap, and desired velocity. These parameters are frequently associated with roadway links of the simulation network such that specific weather and road conditions can be reflected through driving behavior for different parts of the freeway. However, the microscopic driving behavior parameters cannot be matched to weather and road conditions directly, with the exception that look-ahead distance can be used for visibility in weather data. Therefore, driving behavior data under different weather conditions needed to be used to calibrate the driving behavior parameters to implicitly consider the effects of weather and road conditions in microscopic traffic simulations. By using the Wyoming Naturalistic Driving Study (NDS) data sets, Hammit calibrated 10 car-following parameters for seven different weather conditions (Hammit et al., 2019). Similarly, three sets of behavioral parameters were calibrated for three weather and road conditions, including clear, snowy, and severe conditions. The calibration of the parameters will be discussed in the case study section.

By referring to these parameters, a mapping between weather conditions and weather-sensitive driving behavior parameters was created in this study. The AMS tool first receives data on weather and road conditions, and the mapping is used to determine the specific set of driving behavior parameters to use in the simulation evaluation. During the simulation, when the weather and road conditions dynamically change (e.g., changes of the snow intensity or improvement of pavement conditions due to the snowplowing activities), the corresponding driver behavior parameter set should be used.

Simulation of selected weather-responsive management strategies

In this article, three major weather-responsive management strategies are developed, namely early lane change advisory, forward collision warning, and CV-based VSL. In our simulation implementation, CVs receive management strategies through the Traveler Information Messages (TIMs). Each TIM is encoded into a fixed-length string in the component object model (COM) interface. All active TIMs are integrated into one string (TIM packet) and separated by a given separator (e.g., semicolon). CVs decode the TIM packet and update the in-vehicle database.

Forward collision warning (FCW)

FCW systems provide visual, audible, or tactile alerts to warn a driver of an impending collision with a car or object directly in its forward path (Dagan et al., 2004). The warning message can be included as a part of the TIM message and broadcasted to drivers via short-range low-latency wireless communication (e.g., DSRC, C-V2X) and on-board units (OBUs). In the FCW system, the front and rear vehicles are all required to have communication capability and in the communication range of each other, as Figure 2 shows.

In this article, FCW is categorized into two notification levels: cautionary level (yellow) when inverse

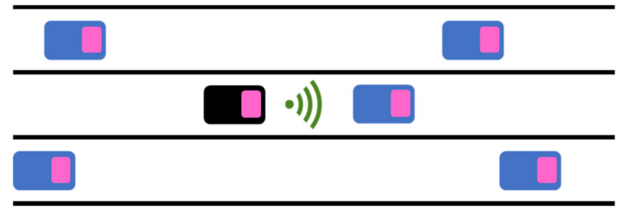

Figure 2. Forward collision warning logic.

time-to-collision (iTTC) is between $0.2\,s^{-1}$ and $0.1\,s^{-1}$ and alert level (red) when iTTC is more than $0.2\,s^{-1}$ (Ahmed et al., 2019). In the cautionary level, there is still sufficient time remaining for drivers to slow down with a reasonable deceleration. However, if the alert level occurs, the FCW system will provide decision-making to help drivers choose between changing their lanes (to the left or right, if there are multiple lanes) and applying the brake heavily. This decision is determined based on the condition of adjacent lanes.

The deceleration and lane change behavior not only need to ensure the safety of the current lane but also the safety of the target lane. Before study CV determines the target lane, it has to ensure the safety of the preceding vehicle and the following vehicle on it (i.e., only when the iTTC between the study CV and the preceding vehicle on the target lane as well as between the study CV and the following vehicle on the target lane are below $0.2\,s^{-1}$ can it be advised to change to the target lane). If the CV has the choice of two target lanes which both meet the safety requirements, the CV will make a stochastic decision under 50% probability (Zhang & Ioannou, 2017)(Zhang Y. &., 2016). These rules replicate regular human driver lane-change behavior and ensure that the safety risks caused by lane changes will not exceed the original risks.

Except for the lane-change decision, another critical parameter to be calibrated is driver deceleration choice after receiving the collision warning (Ahmed et al., 2019). If the warning is at the alert level, the deceleration and lane-change behavior are determined by the VISSIM default car-following and lane-change models because the drivers need to brake heavily or change lanes to avoid crashes. VISSIM can generate reasonable behavior values under this condition. If at the cautionary level, the deceleration may not be directly affected by the front object and, therefore, cannot be accurately captured through VISSIM's models. Therefore, the behavior is calibrated by using a behavior data set collected by the University of Wyoming using a truck driving simulator with 25 professional truck drivers under adverse weather conditions (Ahmed et al., 2019). The average deceleration under

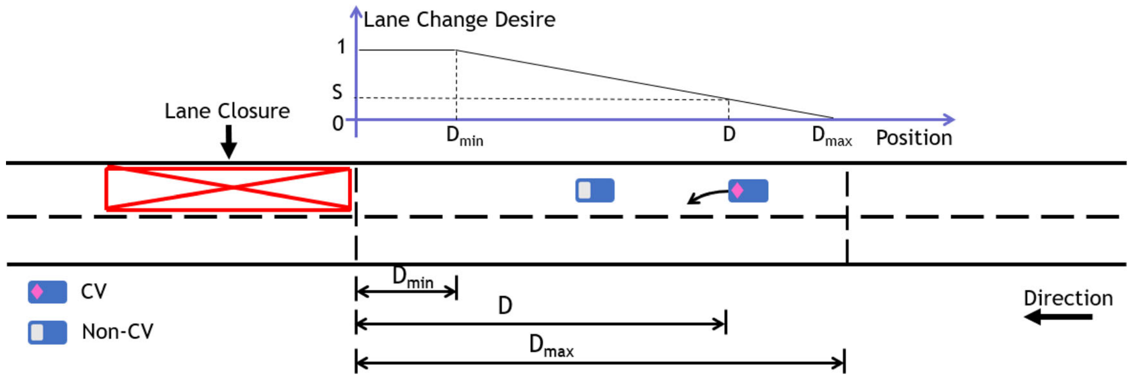

Figure 3. Early lane-change logic.

the cautionary level in this experiment is 0.4 m/s^2 (1.31 ft/s^2). It is regarded as the constant deceleration in this study when drivers receive cautionary level warnings.

Early lane change (ELC) advisory

The ELC advisory is part of the TIM application that provides information about the conditions that exist in a lane closure zone that the host vehicle is approaching (illustrated in Figure 3). This capability provides approaching vehicles with information about lane closure activities that could present unsafe conditions for the workers or the host vehicle, such as obstructions in the vehicle's travel lane, lane closures, lane shifts, or speed reductions.

The idea behind the early lane change advisory is similar to the early lane merge system. Both strategies encourage traffic to merge earlier than it does under conventional lane merge (CLM) configuration. Early lane merge (Beacher et al., 2004; Tarko et al., 1998) typically uses a sequence of "DO NOT PASS" signs that can be activated/deactivated depending on traffic to create a no-passing zone of varying length. The purpose of the no-passing zone is to encourage drivers to switch to the open lane upstream of the end of the dynamically changing queue to improve safety and efficiency. Unlike the early lane merge, the ELC system sends a lane merge signal directly to the drivers within the DSRC communication range through the human-machine interface installed on the CV.

To model the compliance of CV drivers to the ELC advisory, the lane change desire is considered to control the merge decision of the CV driver. The lane change desire represents the probability of the merging behavior at a certain distance ahead of the lane closure zone. As shown in Figure 3, It is defined as a function of the lane-change distance, the distance from the front bumper of the vehicle to the beginning of the lane-closure zone. The smaller the lane change distance, the higher the lane-change desire would be, and the more likely the vehicle would merge into the open lane. The upper and lower bounds of the lane-change distance are defined as the maximum lane-change distance, D_{max}, and the minimum lane-change distance, D_{min}, separately. The maximum lane-change distance is set as the DSRC communication range. The minimum lane-change distance is a threshold distance that once lower than this value, the vehicle would be facing high crash risks and would immediately make a lane change or yield until there is an opening in the open lane traffic. The minimum lane change distance is determined by the speed limit near the lane-closure zone and the inverse time to collision (iTTC) corresponding to the alert level forward collision warning. For example, if the DSRC communication range is 300 meters (984 feet), the speed limit near the lane closure zone is 72 km/h (45 mph), and the iTTC corresponding to the alert level forward collision warning is 0.2 s^{-1}, then the D_{max} and the D_{min} would be estimated as 300 meters (984 feet) and 100 meters (330 feet), respectively. The lane-change desire is defined as in Eq. (1)

$$S = \frac{D_{max} - D}{D_{max} - D_{min}} \quad (1)$$

Where D = early lane-change distance, D_{max} = maximum early lane-change distance, D_{min} = minimum early lane-change distance.

The maximum lane-change distance is set as the short-range wireless DSRC communication range. Specifically, in the case study of this article, the DSRC radios broadcast at a range of 300 meters and operate continuously while the vehicle is in operation (Gopalakrishna et al., 2018). This indicates that once the distance between the approaching CV and the lane closure spot is less than 300 meters, the CV will be informed that there is a lane closure event 300 meters ahead of it. In the meantime, the advisory informs the CV driver which lane is open and

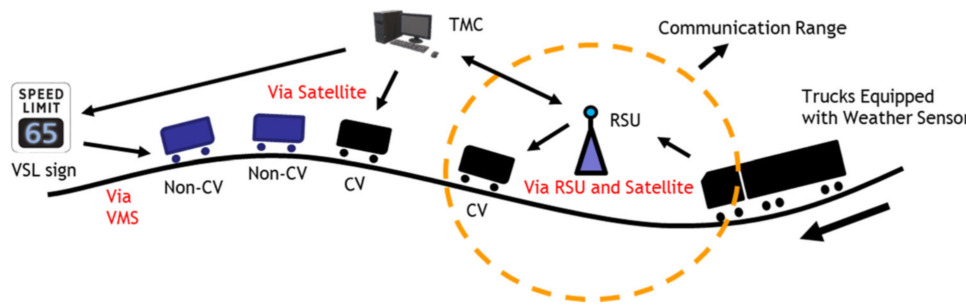

Figure 4. Connected vehicle-variable speed limit system using satellite communication.

suggests the vehicle make a lane change to the open lane if the current lane is closed. In the case study of this article, the look-ahead distance for three weather scenarios, normal, snowy, and severe are 250 m, 153 m, and 61 m, respectively. That is to say, in either case, the CV drivers are aware of the lane closure earlier than they can see the lane closure event. The CV drivers' compliance to the lance change advisory linearly increases with the distance to the lane closure spot.

The logic of the ELC advisory system is achieved in the simulation like this: (i) Once a CV approaches the ELC advisory range, it would constantly receive a signal to merge into the open lane; (ii) At each time step the host CV generates a random number between 0 to 1 and calculates the lane change desire according to its position; (iii) Once the random number at certain time step is less than the lane change desire, the vehicle would start merging into the open lane when the gap on the adjacent lane is safe.

Connected vehicle-based variable speed limit (CV-VSL)

The speed limit information displayed on VSL signs can only be received by vehicles in the visual range. This range is the visibility of drivers under specific weather conditions. This presents spatiotemporal constraints to drivers to receive the information. CVs can also receive speed limit information via the human-machine interface (HMI) equipped on their vehicles. It is assumed that drivers can more easily access and process this in-vehicle information once the messages are displayed on the HMI. In fact, VSL information can also be included as a part of the TIMs and be transmitted along with others via DSRC from the TMC/roadside units (RSU) to CVs. Additionally, the VSL information can be sent through other wireless communication channels (i.e., satellite and cellular communication) which can enable immediate notification of dynamic speed limits to all CVs and, therefore, further improve system safety performance.

The VSL information is not time-sensitive and can be sent through additional channels, subject to information delay and packet drops, in exchange for systemwide information dissemination. The Wyoming CV testbed also proposes to use satellite communication for this purpose as illustrated in Figure 4. In this scenario, all CVs on the road can receive the VSL information after the TMC broadcasts the speed limit information. Meanwhile, non-CVs can continue to receive the VSL information from roadside signs. It is expected that systemwide information dissemination can significantly enhance safety performance, and therefore this dissemination approach is targeted in this study.

The CV-VSL evaluated in this study shares the similar operational process of the current sign-based VSL deployed along Interstate 80 (I–80). One key difference is that CV weather data from snowplow trucks, which are equipped with weather sensors, can be communicated to the TMC once the snowplow trucks are within the communication range of RSUs, particularly in urban areas where RSUs are densely deployed. These real-time data can be utilized by TMC to make decisions on dynamic speed limits promptly, as compared to the conventional data source of sparse road weather information system (RWIS) stations and delayed weather and road condition reports from the field staff. Data from RWIS (i.e., fixed-point data) and connected snowplow trucks (i.e., mobile observations) should be seamlessly integrated to provide a more accurate picture of real-time road weather conditions.

In this article, we use the same weather-responsive VSL decision strategies that are currently adopted in the Cheyenne TMC, as shown in Figure 5. This RWIS speed logic diagram takes data from RWIS and field staff reports as inputs and automatically calculates suggested speed limits under specific weather and road conditions. The key weather parameters included in the diagram are road surface status, humidity, average wind speed, and visibility. Note that, to

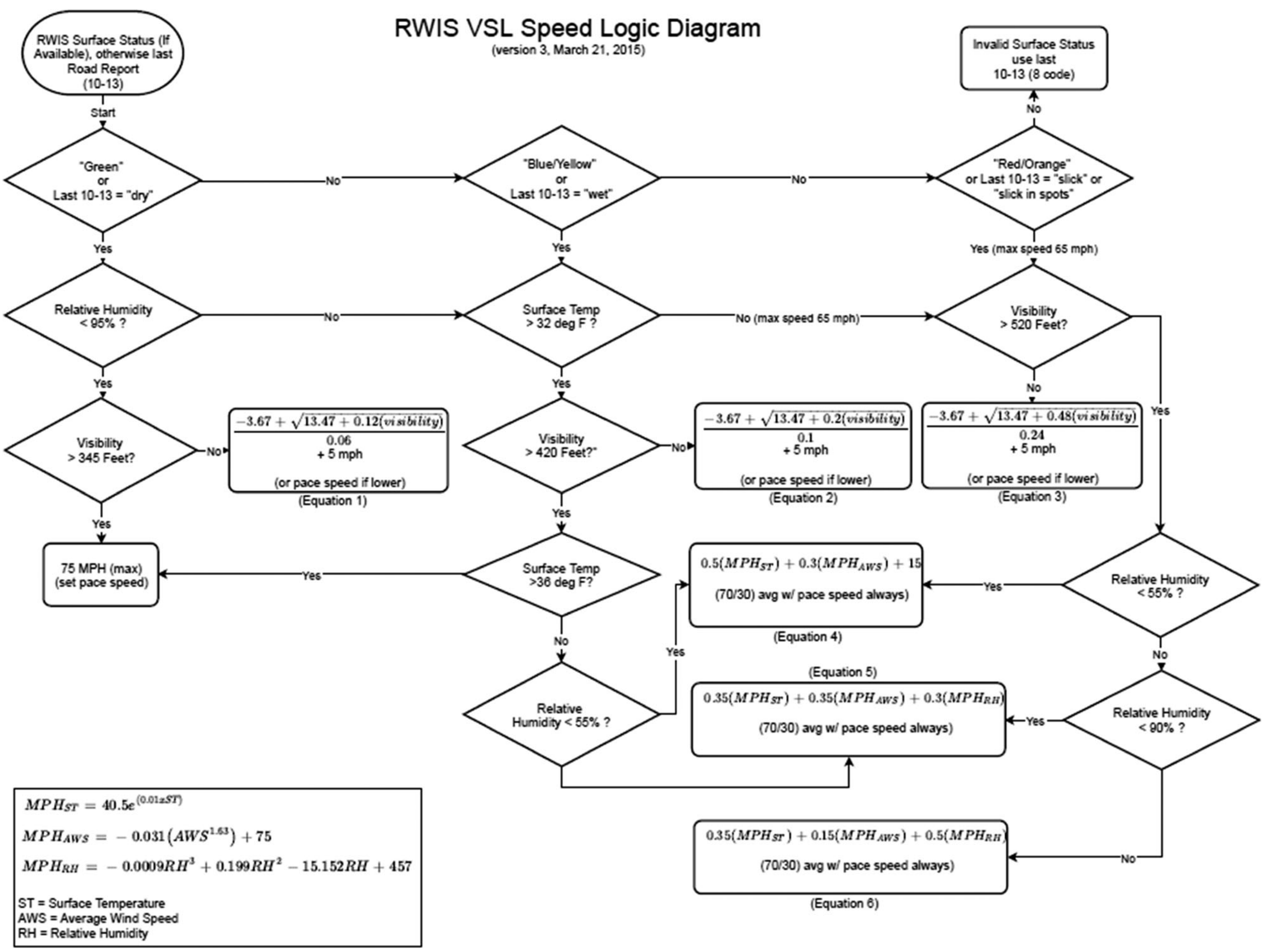

Figure 5. Road weather information system variable speed limit speed logic.

implement this algorithm in the weather-sensitive simulation, the weather and road conditions used in the diagram need to be categorized and mapped to one of the weather-related driver behavior parameter sets, such that the changes of weather conditions can be reflected.

The whole RWIS speed logic is controlled by four key weather-related variables: pavement condition, relative humidity, surface temperature, and visibility. Among these variables, the pavement condition is a categorical variable that includes three categories: dry, wet, and slick. The other three variables are numerical variables. The RWIS speed limit value is calculated by 6 empirical equations, where each of the equations corresponds to a specific set of constraints determined by the combination of pavement condition, relative humidity, surface temperature, and visibility.

In general, the process of calculating the speed limit under certain weather condition can be like this: 1) Describe the weather condition with the four key weather variables; 2) Find out the proper empirical equation corresponding to this weather condition by comparing the variables with the constraints of each empirical equation; 3) Plugin the values of the weather variables into the empirical equation and calculate the speed limit.

Performance measures

The main goal of the WRMS implementation in this article is to enhance safety performance. It is thought that combining relative space and relative speed as one variable by applying the concept of Time to Collision (Allen et al., 1978) may be interesting from the safety point of view. A similar idea can be found in the study of van Winsum and Brouwer (1997), which used TTC as a variable to study the breaking response of drivers in the following vehicles. On the other hand, other studies have introduced inverse Time to Collision (iTTC) for studying the deceleration response of the following car. Balas (Balas & Balas, 2006) claimed that when the relative speed of two involved vehicles is approaching zero, TTC becomes infinitive and makes the variable discontinuous. Balas concluded that the iTTC presents a useful feature when comparing it to TTC: a direct and continuous dependence with the collision risk. Therefore, this article adopts iTTC as a variable.

In this article, the inverse time-to-collision (iTTC) is defined as in Eq. (2) to measure longitudinal collision risks. Time-to-collision (TTC) is defined as the expected time for two vehicles to collide if they remain at their present speed and on the same path. We use inverse TTC to avoid infinity in numerical computation. The iTTCs that are smaller than or equal to 0 implies no collision risk.

$$iTTC = \frac{V_r - V_f}{P_f - P_r} \tag{2}$$

Where, P_f = position of the preceding vehicle (m), P_r = position of the following vehicle (m), V_r = current speed of the following vehicle (m/s), V_f = current speed of the preceding vehicle (m/s).

For a single vehicle j, the total *iTTC* within the time of traveling through the network is calculated using Eq. (3)

$$iTTC^j_{total} = \sum_{i=1}^{n_{ittc}} iTTC_i \tag{3}$$

Where n_{ittc} = number of time steps that the vehicle has positive *iTTC*, i = single time step.

However, the total iTTC usually does not reflect the real collision risk of a vehicle during the trip in the network, since the longer time a vehicle drives, the higher the total iTTC would be. Thus, for a group of vehicles, we use the time-weighted iTTC to reflect the average collision risk of all vehicles in the group and avoid the impact of the travel time of every single vehicle. This measurement uses the travel time of each vehicle as a weight to average each vehicle's unit iTTC in the network. The time-weighted iTTC, $iTTC_{tw}$, is defined in Eq. (4)

$$iTTC_{tw} = \frac{\sum_{j=1}^{N} iTTC^j_{total}}{\sum_{j=1}^{N} TT_j} \tag{4}$$

Where $iTTC_{tw}$ = time-weighted *iTTC* ($1/s^2$), N = number of all vehicles in the group, TT_j = travel time of vehicle j to complete the trip in the simulation network.

While the $iTTC_{tw}$ can serve as a good measure of the overall collision risks in the system, the aggregated values do not distinguish small collision risks with high or extremely high collision risks, which are more likely to cause actual crashes. Therefore, in this article, the collision risks are further categorized into four levels by iTTC: Small risk ($0 < \text{iTTC} < 0.1\,s^{-1}$), Medium risk ($0.1\,s^{-1} < \text{iTTC} < 0.2\,s^{-1}$), High risk ($0.2\,s^{-1} < \text{iTTC} < 0.3\,s^{-1}$), and Extreme risk ($\text{iTTC} > 0.3\,s^{-1}$). Within each risk level, the iTTC is divided into finer intervals with a resolution of $0.02\,s^{-1}$.

Case study

Simulation network calibration

In 2015, Wyoming connected vehicle pilot (CVP) was selected as one of three locations to test and deploy advanced short-range wireless communication technology for various safety and weather-related CV applications (Gopalakrishna et al., 2015). The test network is a portion of the Wyoming CVP corridor on I–80 between Cheyenne and Laramie (mileposts 317–340, 23 miles). To improve driver safety along the corridor, the Wyoming CVP uses applications that leverage V2V and V2I connectivity to support a flexible range of services, such as advisories, roadside alerts, and dynamic travel guidance, for freight and passenger travel.

Simulation modeling of the segment of the Wyoming I–80 CVP corridor has been completed as part of the Wyoming CVP. The microscopic simulator PTV VISSIM is used for the I–80 testbed simulation modeling. The basic corridor network was uploaded from the standard map data in VISSIM. The roadway geometric data, including the number of lanes, roadway segment lengths, and grades; the location of lane additions and drops; and locations of rest areas and parking areas have been manually coded in VISSIM. The comparison between the specific real-world network and the VISSIM model is shown in Figure 6. Additional detailed traffic control parameters have been incorporated to reflect existing operational conditions better. Key traffic parameters include traffic composition, vehicle dynamics data, posted speed limits, the presence of work zones (including location, length, lane-closure condition, etc.).

In the VISSIM network calibrated as a part of the Wyoming CV testbed study, three types of weather scenarios are designed: normal/clear, snowy, and severe weather conditions (Gopalakrishna et al., 2015). The detailed calibration process can be found in Gopalakrishna et al. (2018). These scenarios can distinguish between different pavement conditions and visibility levels. To reflect driver behaviors under different weather scenarios, parameters in the Wiedemann 99 car-following model under 3 weather conditions in VISSIM are calibrated separately, as listed in Table 1.

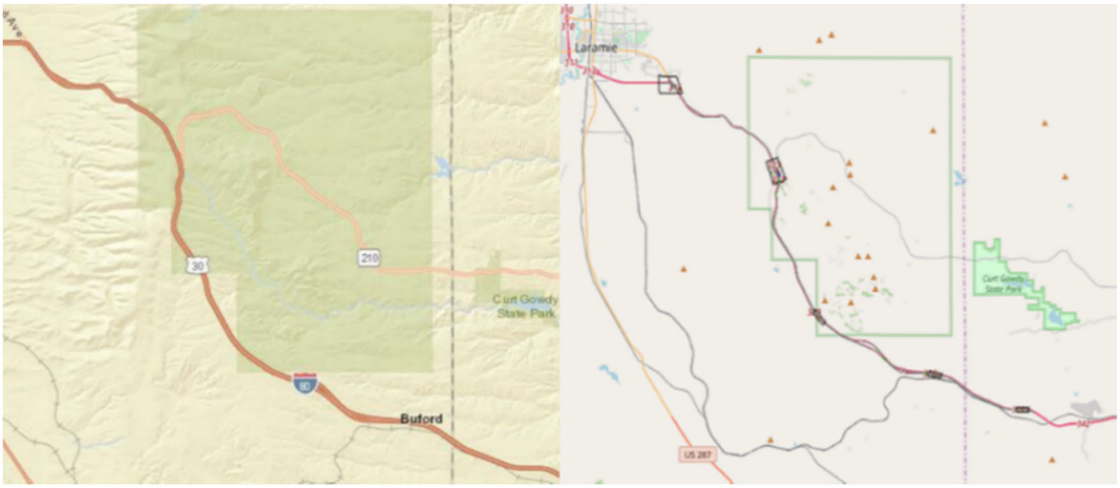

Figure 6. Comparison between the real-world and the VISSIM Network of Interstate 80, Wyoming CVP corridor.

Table 1. Driving behavior parameters under three different weather conditions in the VISSIM network.

Car-following parameter\weather	Normal	Snowy	Severe
Minimum look ahead distance	0.00 m	0.00 m	0.00 m
Maximum look ahead distance	250.00 m	152.40 m	60.96 m
Number of interaction objects	4	2	2
Number of interaction vehicles	99	99	99
Duration of temporary lack of attention	1.00 s	0.50 s	0 s
Probability of temporary lack of attention	10.00%	10.00%	0.00%
Standstill distance for static obstacles	2.44 m	3.05 m	/
CC0	2.44 m	3.05 m	6.10 m
CC1	0.9 s	0.9 s	0.9 s
CC2	4.00 m	6.10 m	6.10 m
CC3	−8.00	−8.00	−8.00
CC4	−0.35	−0.35	−0.35
CC5	0.35	0.35	0.35
CC6	11.44	11.44	11.44
CC7	0.25 m/s^2	0.25 m/s^2	0.25 m/s^2
CC8	3.50 m/s^2	3.50 m/s^2	3.50 m/s^2
CC9	1.50 m/s^2	1.50 m/s^2	0.91 m/s^2

Simulation test scenarios

Different CV MPRs are considered to understand the system performance sensitivity with varying percentages of CVs in the system. In this study, only the HGVs are considered as CVs. The CV MPR is defined as the proportion of CVs in all heavy goods vehicles (HGV). HGVs are the focus of the I–80 CV testbed, which aims to equip trucks with short-range wireless communication capabilities to enhance their operational safety. This is a more realistic scenario in the short term as truck fleet owners are likely to be among the first to utilize CV technologies for safety and efficiency improvements. For all scenarios tested, the MPR of CVs in HGVs is varied from 0% to 100% at a 20% increment. In order to eliminate the confounding effects caused by the traffic volume, the volume in all scenarios is set at the same level as in severe weather conditions. The total simulation time is 7800 seconds, including a 600-second warm-up period. For each scenario, results from 10 random seeds are averaged to account for the simulation stochasticity.

Results

Results of early lane change & forward collision warning

To create external conditions on the network, four active lane-closures are used in the simulation, which is shown in Figure 7. In each of the four events, the right-most lane is closed for 200 m, leaving the left-most lane open for vehicles to bypass the events. Each of the events starts and ends at different simulation seconds, and the duration of time is identical (1 hour) for all lane-closure events. Table 2 shows the parameters for setting the lane-closure events in this study.

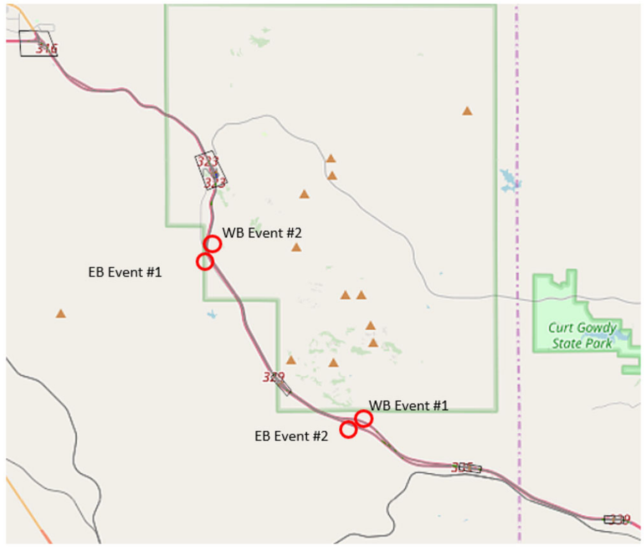

Figure 7. Location of all four road events.

Table 2. Lane closure events settings.

Number	Location(m)	Direction	Start time (s)	End time (s)	Number of lanes closed
EB Event 1	(8,000, −9,190)	Eastbound	600	4,200	1
EB Event 2	(14,000, −16,500)	Eastbound	900	4,500	1
WB Event 1	(14,000, −16,330)	Westbound	1,200	4,800	1
WB Event 2	(8,000, −9,054)	Westbound	1,500	5,100	1

Note that the proposed AMS tool can simulate any type of event with random start/end times.

Figure 8(a) shows the decrease of total iTTC of all vehicles as the CV MPR increases under three weather scenarios. When HGV CV MPR equals 100%, total iTTCs of all vehicles for three weather scenarios decrease by 8.02%, 7.40%, and 19.10%, respectively, as compared to the benchmark total iTTCs (i.e., when the CV MPR is 0%).

As shown in Figure 8(b) and (c), when the CV MPR increases from 0% to 100%, the total iTTC of both passenger cars and HGVs in all three weather scenarios decreases. The descending trend of the total iTTC in HGV cases is more significant because the proportion of CV is only assigned to HGVs. When the CV MPR rises from 0% to 100%, the decrease of total iTTCs for passenger cars is 4.61%, 4.50%, and 12.15% for clear, snowy, and severe weather, respectively. This demonstrates that the increase in the CV MPR helps reduce the collision risks of non-CVs.

Figure 8 also shows that the descending trend of the total iTTC is the most apparent in severe weather cases, indicating that the improvement of system safety performance by increasing the CV MPR is more effective in severe weather conditions.

Figure 9 shows the performance of the $iTTC_{tw}$ of different vehicle types in three weather scenarios. As shown in Figure 9(a), the increase of the CV MPR can also benefit the safety performance of all types of vehicles in terms of $iTTC_{tw}$. When the CV MPR increases from 0% to 100% in the clear weather scenario, the $iTTC_{tw}$ of the passenger cars, HGVs, and all vehicles decreases by 4.64%, 11.92%, and 9.65%, respectively. When the MPR increases from 20% to 100% (0% CV MPR means no CVs), the decrease of the $iTTC_{tw}$ is 12.9% for CVs and 2.51% for non-CVs. Meanwhile, the $iTTC_{tw}$ of CVs is smaller than that of other types of vehicles at all CV MPR levels. This demonstrates that CVs outperform non-CVs in collision risks and provide safety benefits to the entire traffic system.

Similar insights are concluded for the snowy and severe weather scenarios (as shown in Figure 9(b) and (c)). In the severe weather scenario, when the CV MPR increases from 0% to 100%, the time-weighted $iTTC_{tw}$ of the passenger cars, HGVs, and all vehicles decrease by 12.24%, 23.82%, and 19.96%, respectively. When the CV MPR increases from 20% to 100%, the decrease of the $iTTC_{tw}$ is 14.92% for CVs and 11.04% for non-CVs. Similar to the results in Figure 8, the safety improvement in terms of $iTTC_{tw}$ is the most significant in severe weather cases.

Figure 10 shows the average time distribution at each iTTC level during one trip in the network. In all three weather scenarios, a vehicle spends most of the time under low-risk iTTC intervals ($0 < iTTC < 0.1$)

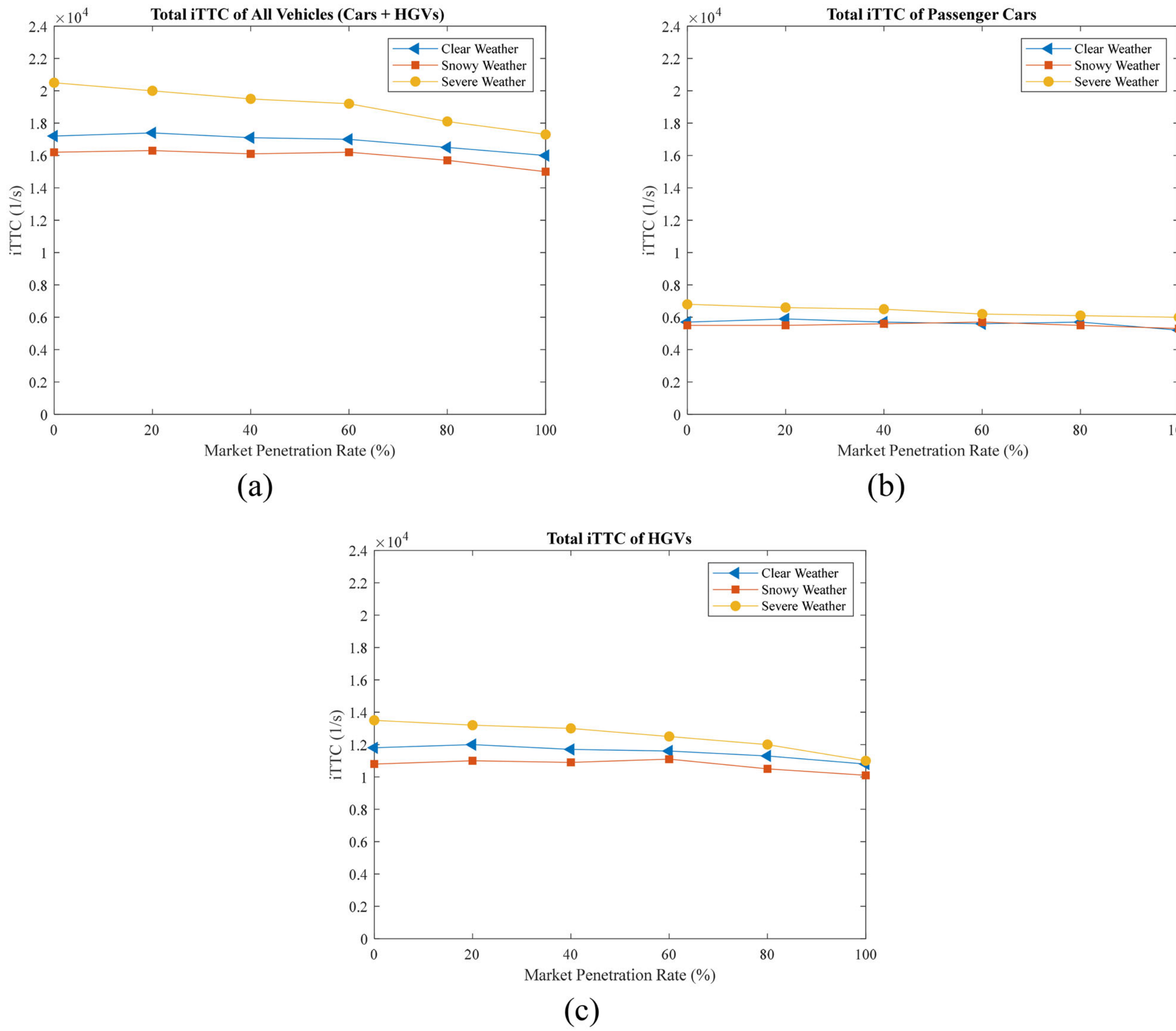

Figure 8. The total iTTC of (a) all vehicles, (b) passenger cars, and (c) HGVs under three weather condition.

and very little time under medium-risk ($0.1 < \text{iTTC} < 0.2$), high-risk ($0.2 < \text{iTTC} < 0.3$), and extreme-risk ($\text{iTTC} > 0.3$) intervals. The clear weather case involves more time at low-risk levels than that in snowy and severe weather cases but has the least time at the medium-to-extreme risk levels. In contrast, the severe weather scenario involves less time at the low-risk iTTC level but much more time at the medium- and higher-risk levels than that in the other two weather cases.

In Figure 10, when the figures are compared vertically with the CV MPR of 0% and 100%, it can be clearly seen that in addition to the overall safety risk reduction, the medium and higher risks with $\text{iTTC} > 0.2$ also significantly decrease. This indicates that the implementation of ELC and VSL can avoid many high-risk near-crashes, therefore considerably improving the overall safety.

Results of variable speed limit

The CV-based weather-responsive VSL is applied in the simulation as follows. The weather change is assumed to take place at the 2,000 th simulation second. The weather condition changes from normal weather to severe weather, which is expected to reflect the safety performance deterioration because of the apparent gap between the desired speed and driving behaviors of vehicles under these two weather conditions. Using the road weather information system (RWIS) VSL algorithm, the determination of the speed limit under three weather scenarios, associated with three calibrated behavior sets (i.e., normal/clear, snowy, and severe) are listed in Table 3. This is a customized mapping between three weather conditions (i.e., simulation behavior sets) and weather parameters used by the VSL algorithm for the purpose of simulation implementation, as discussed in the methodology.

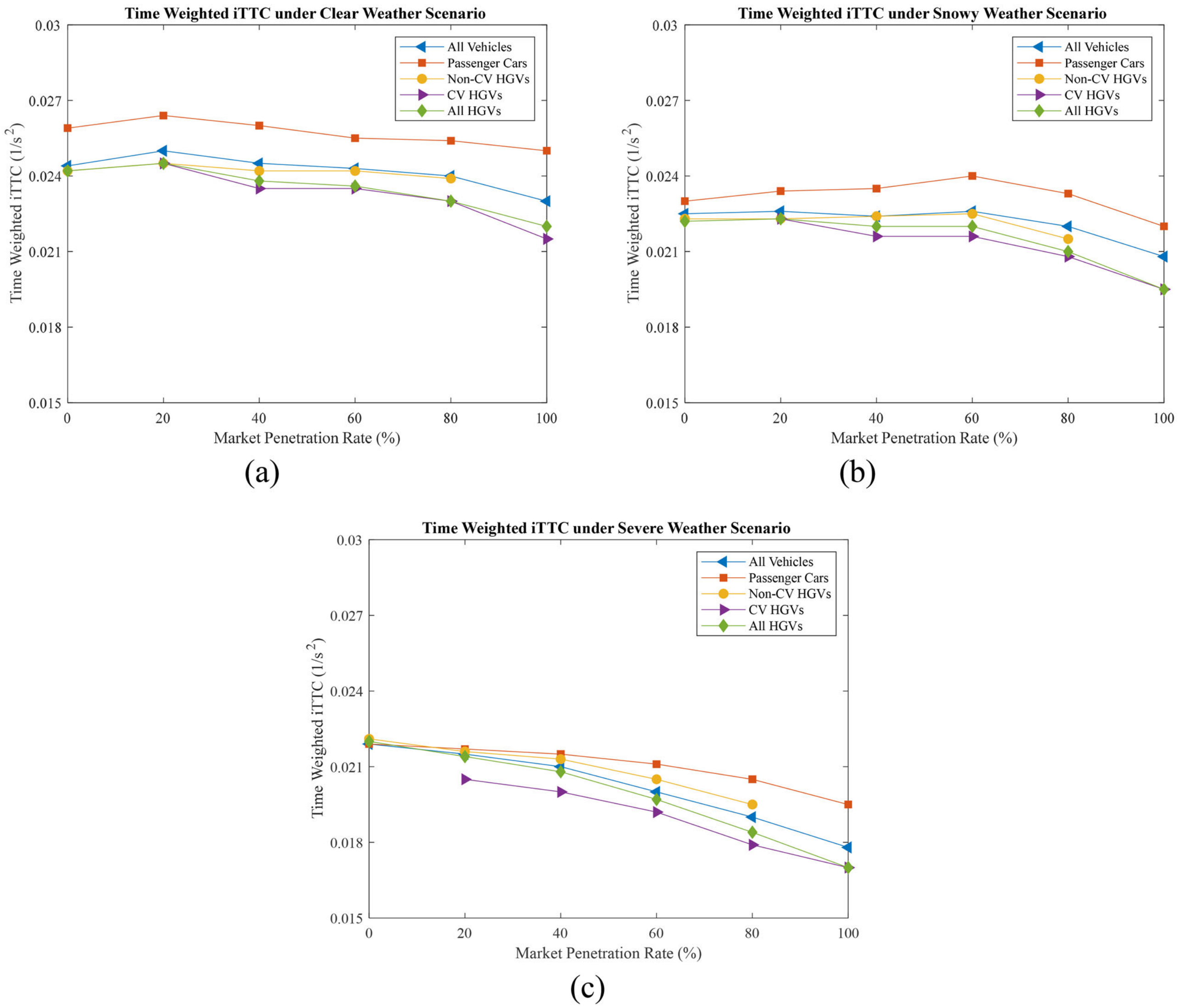

Figure 9. Time-weighted iTTC under (a) clear weather, (b) snowy weather, and (c) severe weather.

In the VISSIM network, to model the VSL sign, the desired speed attribute in VISSIM is modified. The deterministic speed value from Table 3 are used as the desired speed for vehicles under different weather scenarios.

Apart from the VSL, the behavior of non-CVs may also be impacted by CVs that have slowed down due to the latest CV-VSL commands. In this case, the entire traffic can be smoothed by the CVs, even when the CV MPR is low. While this phenomenon has been reported in some literature (Ma et al., 2016), no further information on the influence rate is reported. Therefore, in this report, we adopt a new parameter, traffic-smoothing rate (TSR), to capture the percentage of non-CVs that can be influenced by slow vehicles and conduct sensitivity analysis to understand the effect. The traffic-smoothing rate is a pre-defined parameter, it represents the portion of non-CVs that follows CV's speed after the CV receives the VSL message even if the non-CV itself hasn't seen the VSL sign. This parameter mainly captures the behavior that non-CVs may also be impacted by CVs that have slowed down due to the latest VSL commands. In this case, the entire traffic can be smoothed by the CVs, even when the CV MPR is low. If a vehicle's front vehicle slows down, the vehicle with the traffic-smoothing characteristic will also slow down to continue the car-following maneuver (and the vehicle's desired speed is also changed). Non-CVs not influenced by the front slow vehicles will change their lanes to overtake the slow front vehicle because their desired speed is still high, meaning that they will maintain high speed until they receive the speed limit information from VSL signs. Three levels of TSR selected for testing in the evaluation are 0% (no smoothing effect), 50%, and 100% (full smoothing effect).

Figure 11 illustrates the results of the total iTTC for various scenarios when the CV MPR grows from

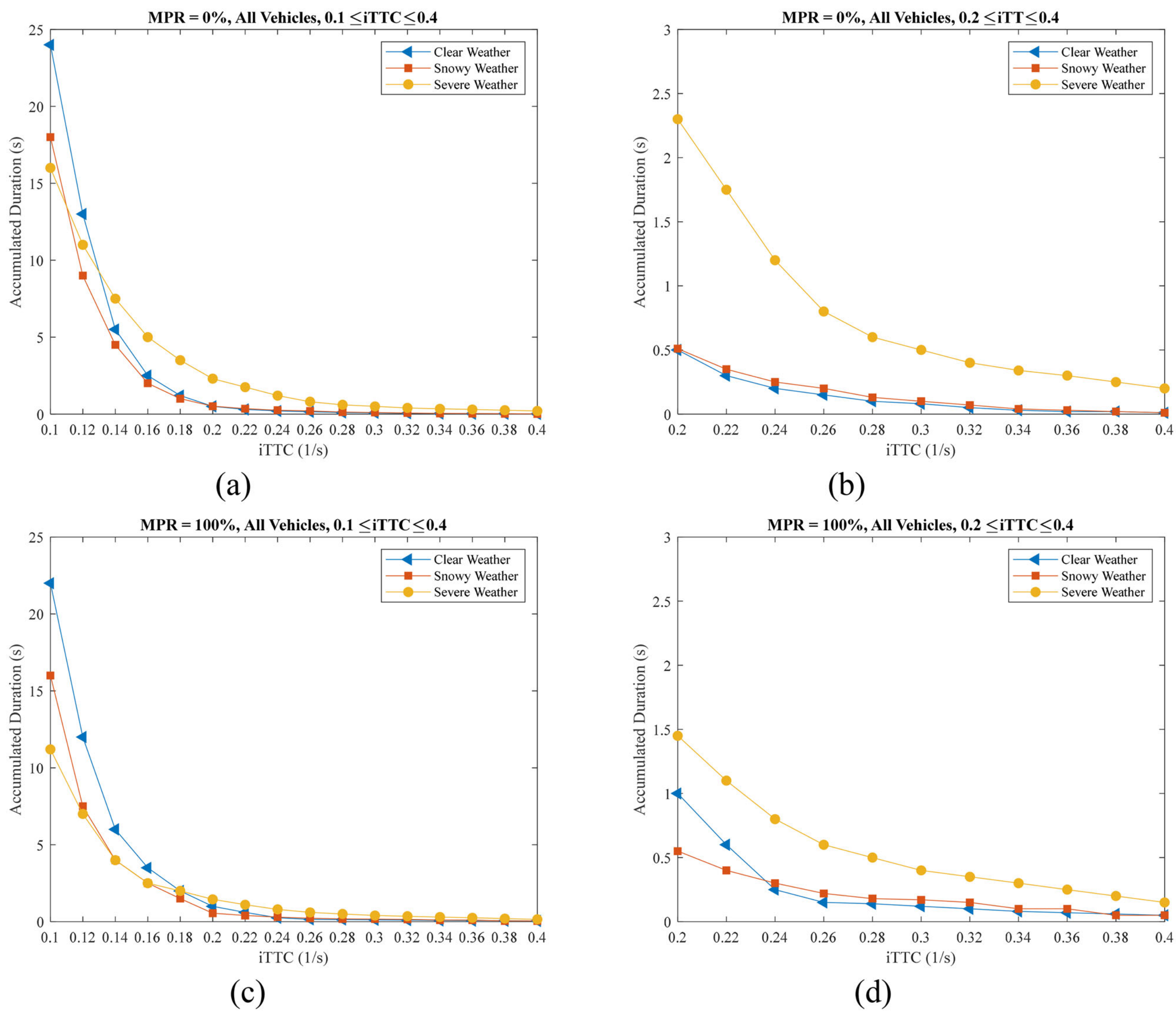

Figure 10. Performance of iTTC distribution between 0% and 100% CV MPR under different weather scenarios: (a) MPR = 0%, $0.1\,s^{-1} \leq$iTTC $\leq 0.4\,s^{-1}$; (b) MPR = 0%, $0.2\,s^{-1} \leq$iTTC $\leq 0.4\,s^{-1}$; (c) MPR = 100%, $0.1\,s^{-1} \leq$iTTC $\leq 0.4\,s^{-1}$; (b) MPR = 100%, $0.2\,s^{-1} \leq$iTTC $\leq 0.4\,s^{-1}$.

Table 3. Speed limit determination of three weather scenarios.

Weather condition (Corresponding to driver behavior)	Pavement condition	Relative humidity (%)	Visibility (feet)	Surface temperature (°F)	Speed limit determination (miles per hour)
Normal	Dry	<95	820	>32	75
Snowy	Wet	<95	500	<32	54
Severe	Slick	<95	200	<32	35

0% to 100%. The results reveal that, for 0%TSR scenarios, the total iTTC increases when the CV MPR grows from 0% to 40%, indicating that the system safety risks become higher. This is mainly because the majority of the traffic on the roads is still non-CVs, and they will continue to drive fast before they see the VSL signs. The interaction between fast non-CVs and slow CVs and maneuvers of lane changes and overtaking may result in many instances of high collision risks. Based on the results in this case study, the peak of the safety risks is reached at 40% of the CV MPR. After 40%, the iTTC curve of the 0% TSR starts to decline because there are a sufficient number of CVs on the road, which are able to block the overtaking maneuvers of upstream non-CVs. Therefore, non-CVs are forced to follow CVs slowly, and the entire traffic is smoothed. Overall, when the CV MPR rises from 0% to 100%, the total iTTC of 0% TSR case decreases by 17.59%.

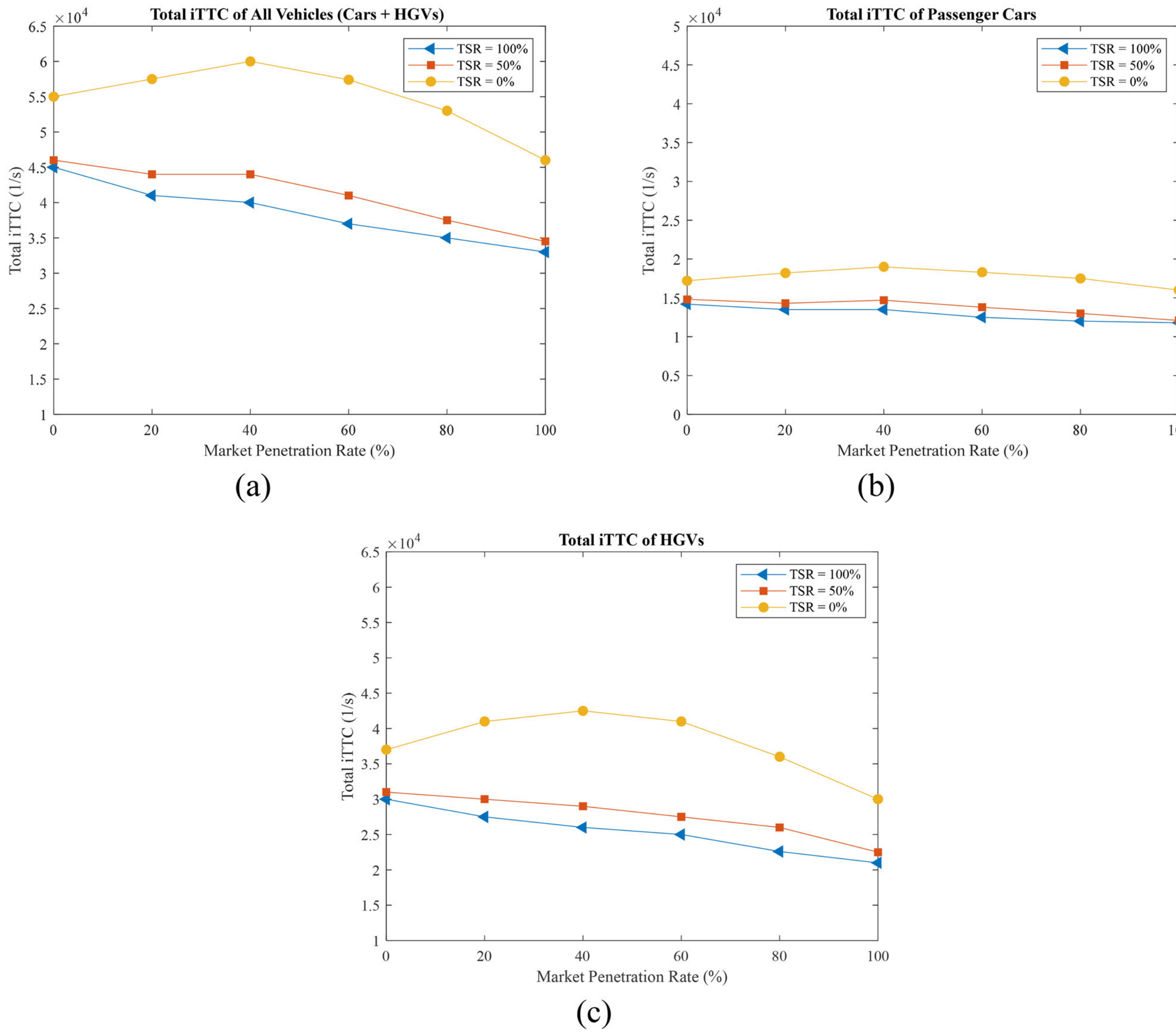

Figure 11. The total iTTC of (a) All vehicles, (b) Passenger Cars, and (c) HGVs under different traffic-smoothing rate (TSR) percentages.

When the TSR is 50% and 100%, the total iTTC drops with the increase of the CV MPR. The decreases in the total iTTC for these two cases when the CV MPR grows from 0% to 100% are 25.37% and 27.24%, respectively. The result indicates that CVs can induce the deceleration of non-CVs that follow the traffic-smoothing rule when the TSR is high. In high TSR cases, when a preceding CV slows down, the following non-CVs will drive more conservatively and tend to follow the new driving behavior of the front CVs. Such phenomena can then spread to the surrounding conservative non-CV vehicles. Therefore, the overall trend of the total iTTC is downward with the growth of the CV MPR in the 50% and 100% TSR scenarios.

It is worth noting that when the CV MPR equals to 0%, the total iTTC under three TSR scenarios are different. When the CV MPR is 0%, the total iTTC decreases with the growth of TSR. This is due to the difference in car-following modes between the three TSR cases. Assume a vehicle slows down when observing a VSL sign (in all scenarios of this report, the assumed compliance rate with the VSL is 100%). If following vehicles are conservative, they tend to follow the deceleration behavior of the preceding vehicle even though the VSL sign is not within the sight distance yet. With more conservative vehicles in the network (i.e., higher TSR levels), the overall car-following behavior is smoother. Therefore, the collision risk of the traffic system can be mitigated with the rise of TSR even if CV MPR equals 0%.

The decrease rate of the total iTTC of passenger cars and HGVs when the CV MPR rises from 0% to 100% under three TSR scenarios are 8.00%, 17.02%, 18.28%, and 21.96%, 29.27%, 31.50%, respectively. The decrease in the total iTTC of passenger cars indicates that when

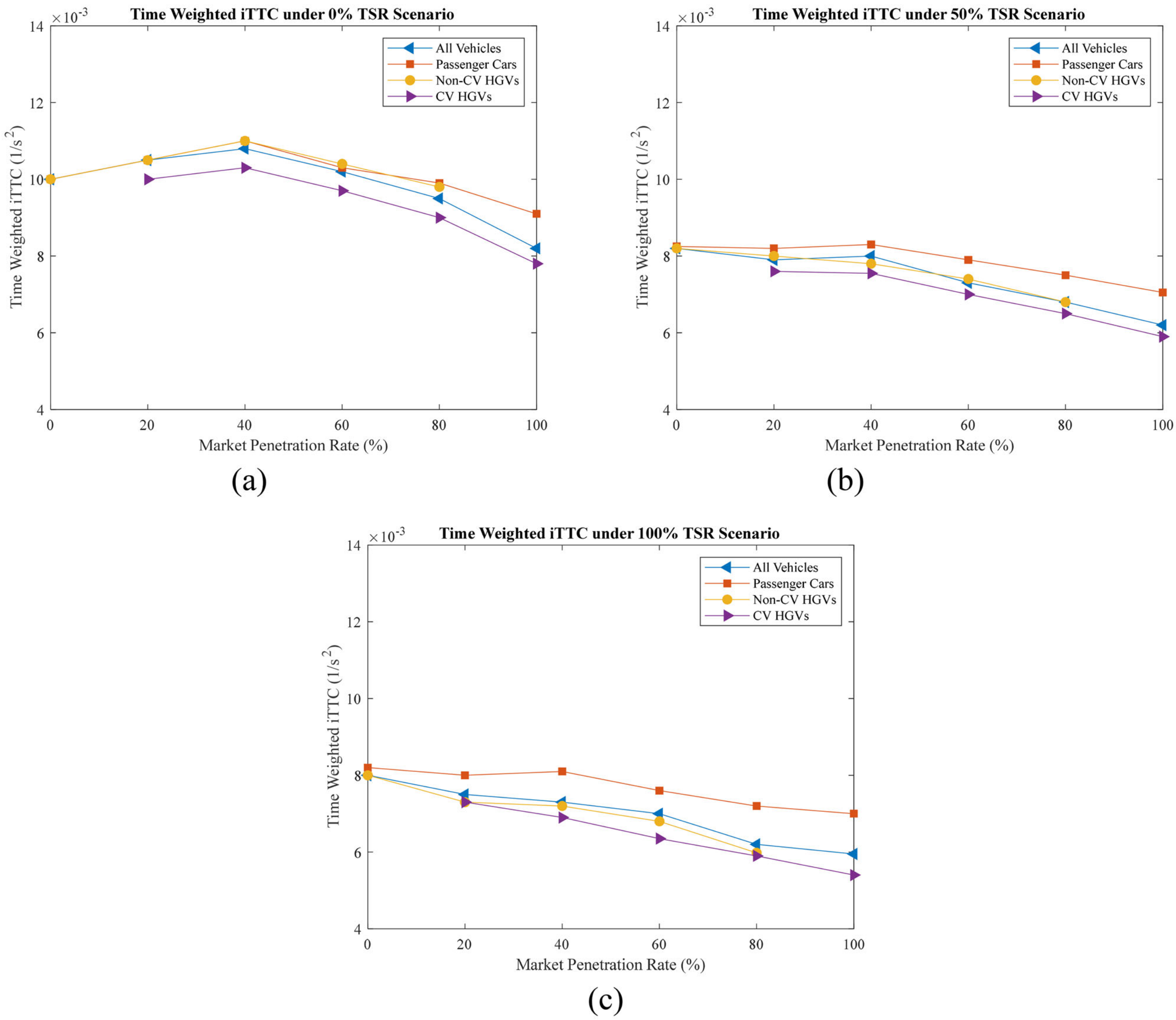

Figure 12. Time-weighted iTTC performance of different vehicle types when (a) TSR = 0%, (b) TSR = 50%, and (c) TSR = 100%.

the TSR is at a high level, CV-VSL can also provide safety benefits to non-CVs whose behavior will not be smoothed unless they are blocked.

Figure 12 illustrates the performances of the $iTTC_{tw}$ of different vehicle types when the TSR is 0%, 50%, and 100%, respectively. For all vehicles in the network, the $iTTC_{tw}$ decreases by 18.00%, 26.29%, and 28.21% in three TSR cases. The comparison of the $iTTC_{tw}$ between different vehicle types shows that when the CV MPR and TSR are the same, CVs outperform non-CVs, reflecting a lower risk of potential collisions.

Conclusions and future research

Summary of conclusions

Adverse weather has a significant impact on the operations of the nation's roadway system year-round. These weather events translate into changes in traffic conditions, roadway safety, travel reliability, operational effectiveness, and productivity. Therefore, it is critical for transportation management agencies to evaluate and implement weather-responsive operational strategies that optimize system performance by mitigating the effects of adverse weather on the roadways.

This study developed customized weather-sensitive AMS tools and investigated the effectiveness of CV-based WRMS in enhancing existing traffic system performance under adverse weather conditions. Three WRMS strategies, ELC, FCW, and CV-VSL were simulated and analyzed with simulations on a real-world corridor, Interstate 80 (I–80) in Wyoming. The simulation results show that the effectiveness of three CV WRMS applications depends on weather conditions, CV market penetration rates (MPR), and the levels of impact of CVs on non-CVs (as quantified by using TSR in the study). Based on the simulation results, multiple key observations and implications are summarized as follows:

- For all scenarios, individual CV-based WRMS applications can improve traffic safety performance, as measured by inverse time-to-collision (iTTC). The effectiveness is most prominent under severe weather conditions.
- A combined application of ELC and FCW can help improve the safety performance of the traffic system by reducing the risk of collisions and the occurrence of pile-up crashes near the lane-closure event zones. In the I–80 case study, the CVs receive multiple advisories from these two implementations to alert the driver to decelerate or make lane changes to avoid potential collisions with the preceding vehicles or objects in the lane-closure zones. The simulation results indicate that the safety benefits provided by CVs continue to increase as the CV MPR rises.
- VSL can provide suitable speed limit advisories under different weather scenarios to keep vehicles driving at safe speeds. The weather information and road conditions can be obtained by RWIS stations as well as vehicles equipped with weather sensors and used to determine the safe speed limits correspondingly. The effectiveness of CV-VSL is influenced by both CV MPR and TSR. The safety performance improves with the rise of CV MPR at each TSR level. Meanwhile, the high TSR cases outperform the low TSR cases in safety performance as measured by the $iTTC_{tw}$ of the traffic system under the same CV MPR.

Contributions

The contributions of this article can be summarized as follows:

- This study proposed three CV-based WRMS strategies that utilize the benefit of V2V and V2I communication and aim to improve safety performance under adverse weather conditions. The effectiveness of the three strategies is further proved to be prominent under different weather conditions with microscopic simulations.
- This article developed a set of simulation methods for building up the mapping relation between the weather condition and vehicle behavioral settings into the microscopic simulation platform. This study also developed a simulation environment based on a real-world network of I-80 and created multiple weather scenarios for testing.
- This study evaluated the effectiveness of employing CVs under different simulation environments that are based on real-world scenarios. The research also studied how the envisioned market penetration rates would affect the improvement of system benefits of CV in terms of reducing collision risk. The quantified benefits of adopting the CV-based WRMS offer a useful reference for policymakers and traffic management agencies to improve the system safety performance.

Limitation and future work

Multiple areas of future work, including research and deployment, are recommended below to further enhance the state of the practice and state of the art in the use of analysis, modeling, and simulation (AMS) tools for WRMS decision-making.

- This study mainly focused only on the longitudinal collision risk of HGVs, given that the lateral collision risk is not the major cause of accidents in the selected I–80 corridor. However, it is still important to consider the lateral effect on the total safety performance. Future study regarding WRMS and lateral safety risks is necessary for gaining a complete evaluation of how the application of CV technologies influences highway safety.
- The selected testbed in this case study has a traffic safety focus, and mobility-related performance is not as important. Additional study is needed in regard to how CVs can impact the travel time of the vehicles under different weather conditions. For congested traffic networks with adverse weather events, it would be necessary to fully implement the framework and develop customized simulation solutions, including additional modules such as online estimation and prediction of traffic demand.
- The effect of driver's compliance rate is fully explored. Although for each CV strategy, we designed different CV MPRs to reflect the different fractions of CVs, the level of compliance of CV derivers upon receiving the advisory information is not quantitatively specified. With this in view, future studies will aim to investigate the effects of compliance to the CV applications under different weather and CV MPR conditions.

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Disclosure statement

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