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Systematic Evaluation of a Connected Vehicle-Enabled Freeway Incident Management System

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Abstract: Freeway incidents block road lanes and result in increasing travel time delays. The intense lane changes of upstream vehicles may also lead to capacity drop and more congestion. Connected vehicles (CVs) offer a viable solution to minimize the impact of such incidents via monitoring the status of the incidents and providing real-time driving guidance. This paper evaluates the performance of an existing CV-enabled incident management system, which minimizes travel time by effectively leading CVs to bypass incident spots. This study comprehensively quantifies the effects of system parameters (speed weight and lane-changing inertia), control segment length, and road information-updating intervals. This analysis identifies the optimal settings for the incident management system to minimize vehicle travel time delays. Additionally, this paper evaluates the influence of CV market penetration rates (MPRs), network volume-to-capacity ratios, and incident settings to understand the system benefits under varying connected environments and traffic conditions. The results reveal that with the control of the proposed system, overall travel delays can be reduced by up to 45% and that road congestion caused by incidents can be mitigated quickly.

Keywords: connected vehicles; incident management; travel time delay; lane changes; market penetration rates; congestion levels

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1. Introduction

Road events, such as car incidents and road constructions, often lead to road closures with one or multiple lanes. Vehicles traveling upstream of the closures must change lanes to avoid blocked areas. However, the significant speed difference between closed and open lanes makes it challenging for vehicles in blocked lanes to merge, causing them to queue behind closures. In addition, the high volume of lane changes near these events leads to a capacity drop [1]. Hence, these factors create severe congestion and make it difficult for drivers in the queue to decide when and where to change lanes to avoid delays. This highlights the urgent need for an advanced driver assistance system (ADAS) to guide queued vehicles in selecting optimal lanes at the right time, minimizing travel time delay, and improving traffic flow.

The development of the ADAS system for road events requires a good understanding of vehicle lane-changing behaviors. In the literature, numerous models [2–7] have been developed to describe mandatory and discretionary lane changes as the functions of the relative locations and speed of vehicles in adjacent lanes to subject vehicles. However, if there is an incident on a road, these models are not sufficient to help upstream drivers to find the optimal lanes to take, with drivers needing more information to overpass the incident with small delays. To minimize the negative impact of incidents, the variable message sign (VMS) method was developed to show real-time road incident information for all vehicles on roads to make lane-changing decisions before they enter a congested region. This information was proven to be very useful to minimize the delay of individual vehicles. However, in real-world implementations, only a few drivers would change their behaviors even after seeing this message [8]. Moreover, some improved VMS systems [9–12] could even estimate lane-changing instructions for individual vehicles to control traffic on all open lanes to mitigate upstream congestion on roads, although these systems had limited applications for narrow roads with a small number of lanes and it was very complicated to deploy them on wider roads. Moreover, the effectiveness of VMS systems was notably constrained by their fixed message sign locations, limiting their applicability in managing unexpected traffic congestion caused by incidents at random locations and at random times on roads.

Recently, with advancements in connected vehicle (CV) technology, innovative management systems have been widely investigated to mitigate the impact of non-recurrent congestion caused by road incidents. These systems leverage onboard sensors such as cameras, radar, and lidar installed in CVs to detect and monitor critical incident details, including location and lane closures, enhancing real-time traffic management. Most studies on CV-enabled lane-changing assistance focus on monitoring the dynamics of surrounding vehicles and identifying optimal gaps for safe lane changes [13,14]. For example, Toledo et al. [7] developed a target lane choice model that assigns utility values to lanes based on attributes such as density, speed, and the presence of heavy vehicles, selecting the lane with the highest utility as the target. However, this model does not incorporate CV technologies, nor is it designed to address challenges posed by road incidents. Moriarty and Langley [15] utilized information collected by in-vehicle sensors to monitor road traffic conditions and applied supervised and reinforcement learning algorithms to instruct CVs' change to lanes with higher speeds. Jin et al. [16] developed a real-time lane selection system by leveraging CVs to optimize lane-level paths for individual vehicles, aiming to minimize travel times and enhance fuel efficiency. The system utilized CVs to monitor real-time vehicle dynamics, including locations, speeds, and lane positions, as well as to estimate and recommend the most efficient lanes with high speeds for CVs. Similarly, Ye and Ramezani [17] proposed a lane distribution optimization method with both CVs and autonomous vehicles to minimize freeway congestion. Moreover, a CV-based lane-changing advisory system was developed to search for the optimal lane with the highest speed utility for each CV to overpass downstream congestion with smaller delays. All the aforementioned studies were proven to be very effective in reducing road congestion with lane-changing instructions for CVs. However, they rarely discussed the immediate solutions to road incidents.

In the literature, one pioneer solution for the problem was proposed in [18], where an innovative incident management system, lane-changing assistant (LCA) system, was developed to assist CVs in making lane changes to overpass downstream incidents and to mitigate the corresponding congestion to improve the mobility of the other non-CVs. In the system development, CVs were applied to monitor road incident statuses and the dynamics of individual vehicles. These data were used to calculate an index to represent the speed of each lane for each CV. Based on these speed indices, the system directed CVs approaching incidents to switch to the lane with the highest speed index, optimizing traffic flow and reducing delays. In [18,19], the system's performance was assessed using microscopic simulations, which evaluated its effectiveness under various vehicle communication features. These simulations provided detailed insights into how communication parameters influenced the system's ability to manage traffic dynamics and optimize lane utilization during road incidents. However, as road incidents can occur unpredictably at any location and time, the real-world implementation of such systems must be highly adaptive and quickly deployable to accommodate varying incidents and traffic conditions. To ensure this adaptability, conducting a sensitivity analysis is crucial to evaluate the system's robustness and reliability under diverse scenarios. This analysis helps identify potential weaknesses and ensures consistent performance across a range of conditions. Additionally, the limitations of system implementation must be clearly investigated, providing a realistic understanding of its operational boundaries and the potential challenges in deployment. In this paper, a more comprehensive evaluation of the proposed incident management system is conducted. The sensitivity of four system parameters (speed weight factor, lane-changing factor, control length, and updating interval) is analyzed to search for the optimal system settings. In addition, the performance of the system under different market penetration rates (MPRs) of CVs, volume-to-capacity (V/C) ratios, and incident settings, is analyzed to understand its reliability at different connectivity environments and traffic scenarios. The sensitivity analysis will provide important guidelines for effective real-world implementations of the incident management system.

In the rest of this paper, Section 2 makes a detailed review of the incident management system developed in [18]. Section 3 analyzes the impact of parameters defined in the system on mitigating incident-induced congestion. Section 4 conducts a sensitivity analysis about MPRs of CVs and congestion levels. Finally, Section 5 summarizes the findings and proposes future directions.

2. Review of the Incident Management System

In this section, we will review an incident management system developed in [18] for systematic performance evaluation. The detailed model development, including the implementation of CVs and the definition of the speed index, will be summarized in the rest of this section.

The incident management system aims to reduce travel time delays for CVs and alleviate road congestion caused by road incidents. To achieve this, the system relies on in-vehicle sensors to collect real-time data on the dynamics of CVs and surrounding vehicles, such as location, speed, and lane position. This information is used to make informed decisions about traffic flow, optimizing routes and lane choices to minimize delays and improve overall traffic management during incidents (see Figure 1). It can also monitor the status of road incidents, such as their locations and blocked lanes. This information will then be applied to calculate the speed utility, $V_{k,l}(t)$ for CV k, to take lane l at time t. Equation (1) shows the definition of the speed utility.

$$V_{k,l}(t) = f_{k,l} \cdot (\mu \cdot S^{p}_{k,l}(t) + (1-\mu) \cdot S^{s}_{k,l}(t)). \tag{1}$$

The speed utility consists of two components: (1) $S^{s}_{k,l}(t)$, safety speed for CV k to change to the lane l at time t; and (2) $S^{p}_{k,l}(t)$, perspective speed of lane l at time t for CV k, which measures the average speed of all vehicles ahead of CV k on lane l. The formula of perspective speed is shown in Equation (2).

$$S^{p}_{k,l}(t) = (\bar{v}_{k,l}(t) + \Delta v_{k,l}(t)) \cdot p^{k}_{l}. \tag{2}$$

The perspective speed shows the speed that CV k will apply to pass the downstream incident with the prediction of the future traffic condition and the penalty of making lane changes. $\bar{v}_{k,l}(t)$ is the weighted average speed of all CVs from vehicle k to the incident on the lane l at time t, and $\Delta v_{k,l}(t)$ is the predicted changes of the average speed ahead of the vehicle k on lane l from time t to $t + \Delta t$. The value of $\Delta v_{k,l}(t)$ is a function of the traffic condition of the segment between CV k and the incident on lane l (see Equation (3)), including the entering flow rate $q^{i}_{k,l}(t)$, the exiting flow rate $q^{o}_{k,l}(t)$, and the flows entering from the left lane $q^{l}_{k,l}(t)$ and right lane $q^{r}_{k,i}(t)$ (as shown in Figure 1).

$$\Delta v_{k,l}(t) = F\left(\rho_{k,l}(t) + \frac{\left(q^{i}_{k,l}(t) + q^{l}_{k,l}(t) + q^{r}_{k,l}(t) - q^{o}_{k,l}(t)\right) \cdot \Delta t}{x_k(t)}\right) - v_{k,l}(t) \tag{3}$$

where $F(\cdot)$ is the speed–density relationship determined by the fundamental diagram of the freeway segment. p^{k}_{l} is the factor of lane-changing penalty, which is

$$p^{k}_{l} = 1 - \beta \cdot |l - l_k(t)|, \tag{4}$$

where $l_k(t)$ denotes as the current lane of the vehicle k at time t. β is the lane-changing inertial factor, which is set to add penalties for lane changes and eliminate unnecessary lane changes for CVs. Basically, with more lane changes, the penalty will be larger, and the vehicle will be less likely to conduct lane changes.

The safety speed, $S^{s}_{k,l}(t)$, is determined by a car-following model with the leading vehicle of CV k on lane l. The factor, μ, varies between 0 and 1 to set the weights of perspective and safety speeds. In Equation (1), $f_{k,l}$ is defined as the penalty of CV k to travel on lane l, and it is determined by the CV's current location and the lane closure conditions, i.e.,

$$f_{k,l} = (L_k/L)^2, \tag{5}$$

where L_k is the distance from CV k to the incident, and L is the length of the segment with the incident management system. When the vehicle is closer to the incident, its speed utilities of blocked lanes will be smaller, and it has a higher chance of being instructed to open lanes.

At every time step t, the incident management system estimates the speed utility, $S^{p}_{k,l}(t)$ for CV k on lane l with Equation (1), and the lane with the highest utility will be selected as the optimal lane for CV k to take. This system enables the CV to make an informed lane-changing decision before entering the congested area, allowing it to maintain a higher speed and pass the incident with minimal delays. By encouraging more vehicles to change lanes earlier and reducing the traffic flow into blocked lanes, the system helps balance traffic distribution across open lanes. This approach significantly mitigates overall congestion, improving traffic flow and reducing delays for all road users.

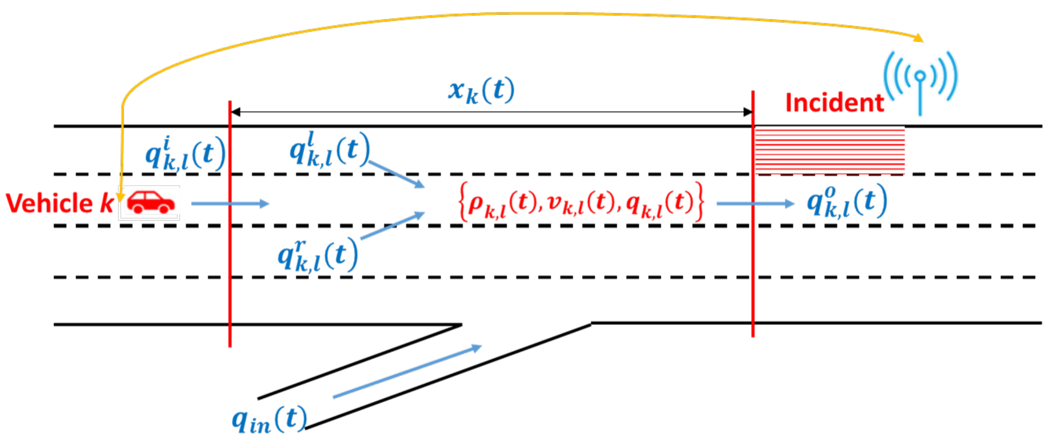


Figure 1. Traffic states at the upstream of one road incident.

3. Sensitivity Analysis of System Variables

In this section, the impact of the variables defined in the incident management system, including the weight factor of the perspective speed, μ, the lane-changing inertial factor, β, the control length, L, the updating interval, Δt, and the market penetration rate (MPR), will be evaluated to understand the system reliability.

3.1. Simulation Settings

To conduct the sensitivity analysis, the system will be implemented in a freeway segment with microscopic simulations. Figure 2 shows the geometry of the simulated network, which consists of a 7500 m mainstream freeway and a 300 m on-ramp. The on-ramp merges with the freeway at a distance of 3000 m. The settings of the freeway and on-ramps are shown in Table 1.

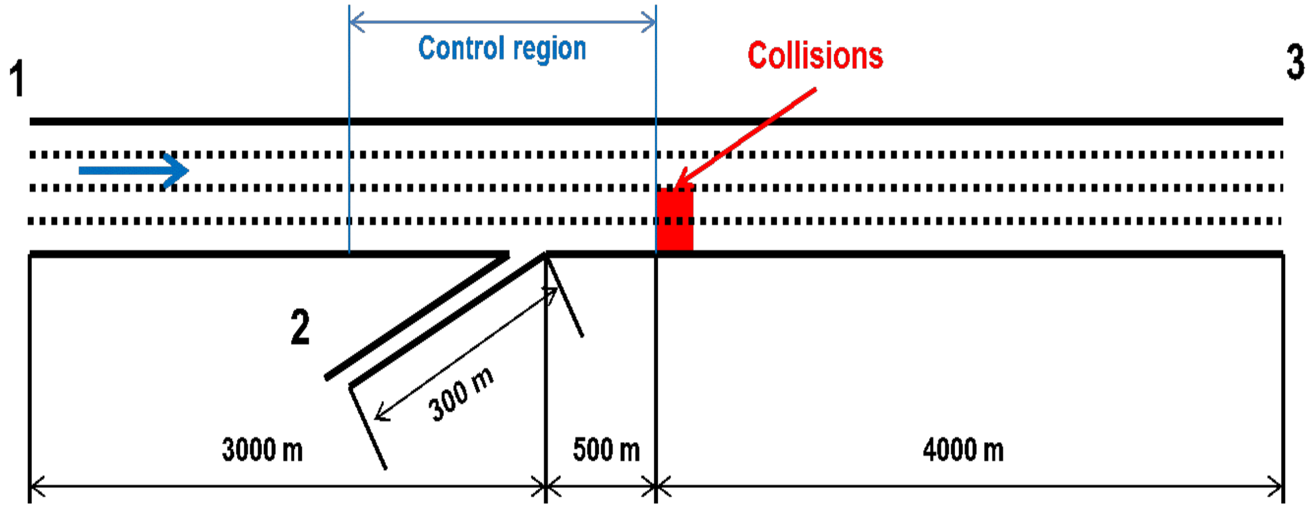


Figure 2. Network geometry (Traffic is loaded from Origins 1 and 2 to Destination 3).

Table 1. Network settings.

Variables	Freeway	On-Ramp
Capacity (vph/lane)	2100	1800
Free-flow speed (km/h)	108	80
Speed at capacity (km/h)	90	70
Jam density (veh/km/lane)	160	160

In the simulations, the vehicles are loaded to the network at two origins, 1 and 2, and they all exit at destination 3, while CVs are only loaded into the network through the origin 1. The flows entering origins 1 and 2 are set as 3500 vph and 1000 vph, respectively. The overall flow is close to the capacity of the freeway segment, resulting in serious road congestion when the freeway is partially blocked by the incident. The simulation will run for 90 min for all scenarios in the sensitivity analysis, while the demands are only loaded for the first 50 min; in the remaining 40 min, the demands are set to 0 to evacuate the network.

The INTEGRATION microscopic traffic simulator [20,21] is applied to simulate the traffic in the network. The simulator applies the RPA car-following model [22,23] to simulate the dynamics of each vehicle, and it tracks the movement of each one of them every 0.1 s. In addition, INTEGRATION is an open-source software, which allows us to model different control strategies of CVs. In this study, the proposed incident management system is modeled in the simulator with the information collected by all connected vehicles for speed utilization estimation, and the optimal lane instructions are also given to all CVs to avoid incidents.

In the simulation, we arbitrarily set one incident at 4000 m upstream of the freeway exit, at node 3. The start time of the incident is $t = 600$ s, and it will block the right two lanes and the last one for 40 min. When an incident is activated, all vehicles traveling in the right two lanes upstream of the incident must shift to the left lanes. This lane-changing requirement ensures that vehicles can bypass the blocked area, although it may lead to congestion if not managed effectively. The proposed system will use CVs to detect the incident (identifying its location and status) and share information with the other CVs running in the network to estimate optimal lane selections.

Note that, in this study, the vehicular communications among CVs are fast and stable, i.e., the latency is set as 0 s, and the package loss ratio is set to 0% to simplify the communication model.

3.2. Sensitivity Analysis of Weight Factors

In this subsection, a sensitivity analysis about two weight factors, the speed weight factor μ and the lane-changing inertial factor β, is conducted to find their optimal values in order to maximize the performance of the incident management system. This case study applies the same simulation settings in the aforementioned subsection.

In the proposed system, the speed weight factor, μ, is introduced to balance the influence of the perspective speed and the safety speed when determining speed utility. A higher value of μ places greater emphasis on the perspective speed, encouraging CVs to prioritize lane changes toward lanes with higher speeds. On the other hand, the inertial factor, β, is used to impose a penalty on lane-changing behavior. Larger values of β increase this penalty, thereby encouraging CVs to maintain their current lanes, reducing unnecessary lane changes. These two factors, μ and β, play a crucial role in shaping the overall behavior of the system. Careful tuning of these parameters is essential to strike a balance between maximizing mobility and maintaining safety and stability. Proper calibration can significantly enhance the system's performance by ensuring optimal decision making for lane changes while minimizing risks and disruptions in traffic dynamics.

Figures 3 and 4 illustrate the average delay experienced by CVs and all vehicles (including both CVs and non-CVs) under varying values of the speed weight factor, μ, and the inertial factor, β, respectively. The analysis reveals that when μ is small and β is large, the average delay for CVs and all vehicles is high. In this scenario, the system strongly discourages lane changes, causing CVs to remain in their current lanes. As a result, the open lanes are underutilized, limiting the system's ability to alleviate congestion caused by the incident. Conversely, when μ is large and β is small, CVs engage in more frequent lane changes. While this initially improves traffic flow, it can quickly lead to congestion in open lanes, thereby diminishing overall road mobility. From the two figures, the combination of $\mu = 0.94$ and $\beta = 0.07$ yields the lowest average delays for both CVs and overall traffic. Specifically, under this parameter setting, CVs experience an average delay of 97.3 s, while the average delay for all vehicles is 105.7 s. When compared to the base case, these values represent significant reductions in delay: 16.2% for CVs and 6.7% for all vehicles. This demonstrates the system's effectiveness in optimizing traffic flow and minimizing delays, particularly for CVs, which benefit more substantially from the improved lane-changing strategy.

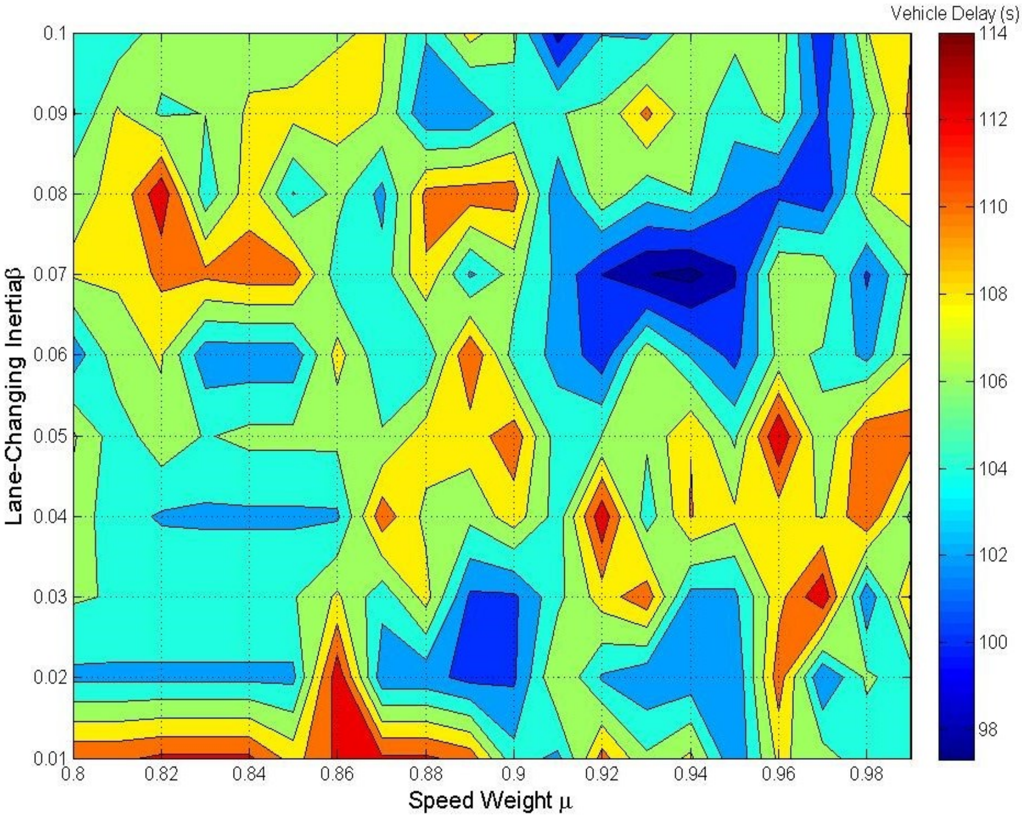


Figure 3. Average delay of CVs under different speed weights and lane-changing inertial factors.

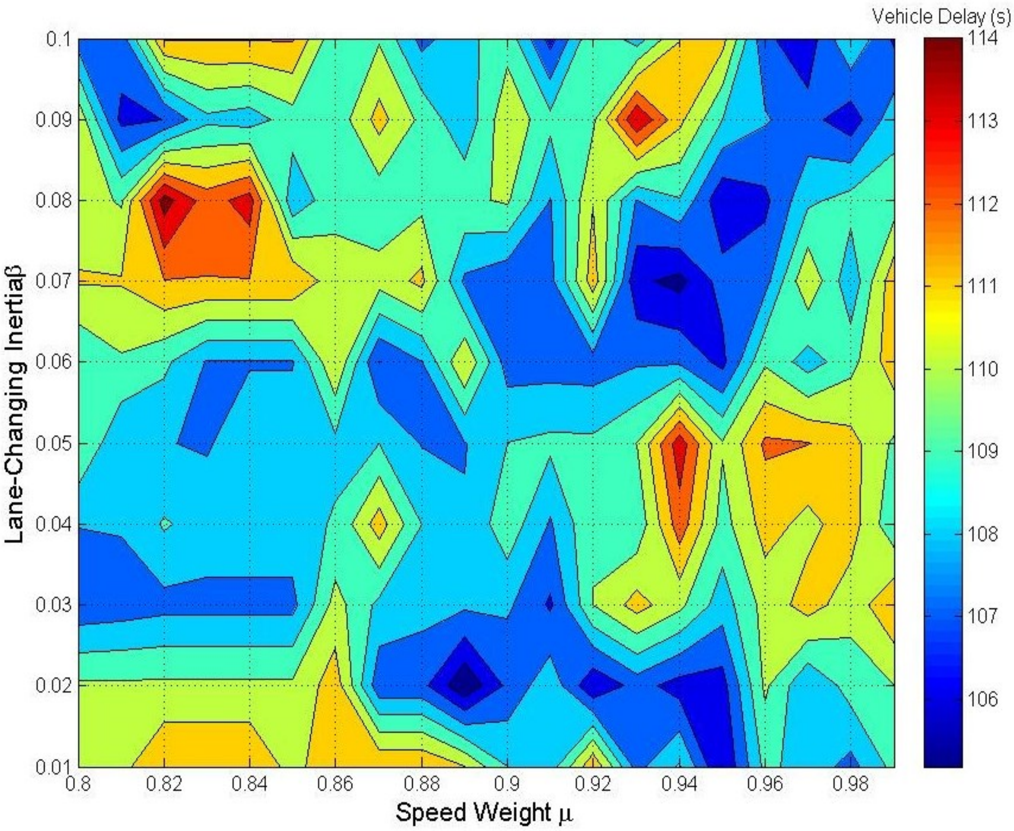


Figure 4. Average delay of all vehicles under different speed weights and lane-changing inertial factors.

3.3. Sensitivity Analysis of Control Length

In this subsection, the influence of the control region's length on the incident management system's performance is examined. This length affects system performance in two main ways. First, with a longer control region, more CVs can be controlled, and they will have earlier instructions to pass the incident. On the other hand, if the region is too long, there will be more unnecessary lane changes upstream of the incident, which will reduce the performance of the whole road. In that sense, there shall exist an optimal control length to maximize the system benefits.

Figure 5 illustrates the average delays of on-ramp vehicles, CVs and non-CVs on the freeway, and all vehicles under different values of control length. The results indicate that the optimal control length is 1000 m to minimize the delay of all vehicles. Meanwhile, the delays of ramp vehicles, freeway CVs, and non-CVs are also minimized. The figure also shows that both higher and lower values of the control length can reduce the benefit of the system.

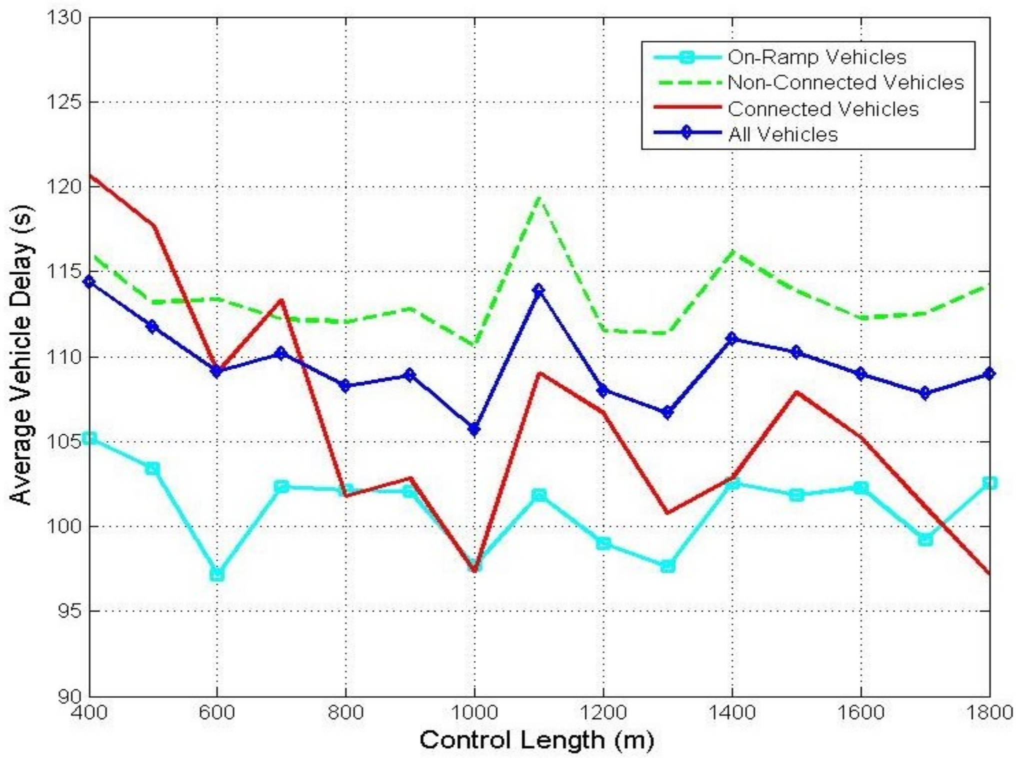


Figure 5. Average delay under different control lengths.

3.4. Sensitivity Analysis of Updating Interval

This subsection examines the impact of the instruction-updating interval on the performance of the incident management system. It is anticipated that the shorter intervals can help CVs respond to incidents with smaller latencies, enabling them to always choose the best lanes to pass an incident faster. However, intervals that are too small will result in frequent lane changes and in a low driver compliance rate. This will constitute smaller savings in travel time delay from the system. Hence, there exists an optimal value of the updating interval to maximize the performance of the system.

Figure 6 compares the average delays of on-ramp vehicles, CVs and non-CVs on the freeway, as well as all vehicles under different values of the updating interval. The results indicate that a 10 s interval can minimize the travel time delays of all vehicles. Compared with the base scenario, the delay is reduced by 4% for all vehicles and 10% for CVs.

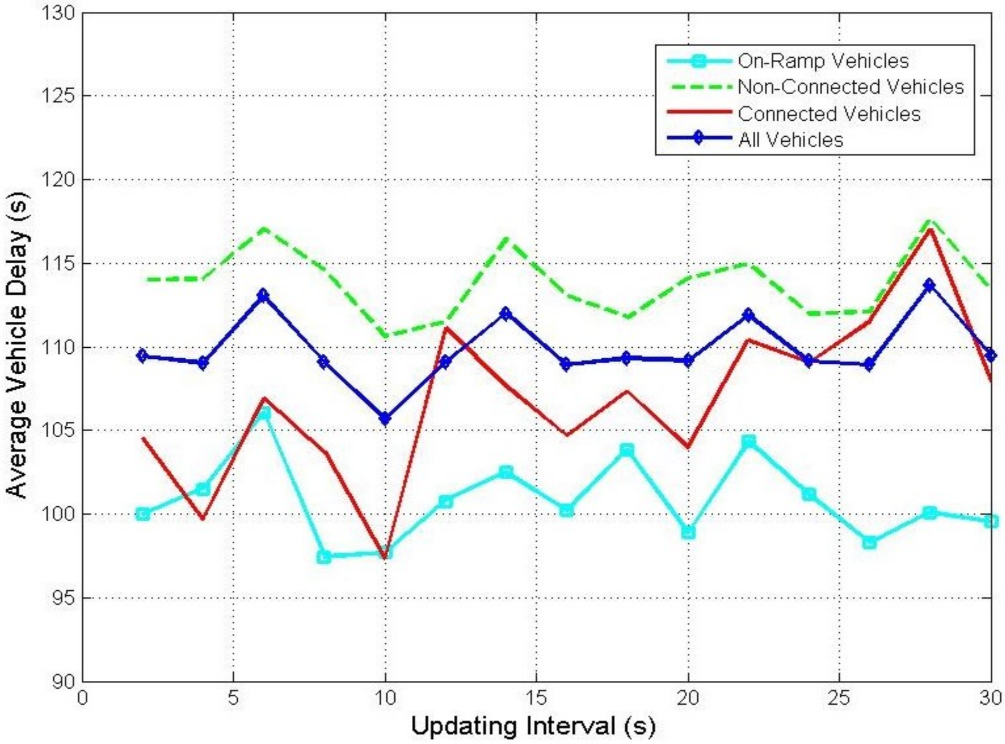


Figure 6. Average delay under different updating intervals.

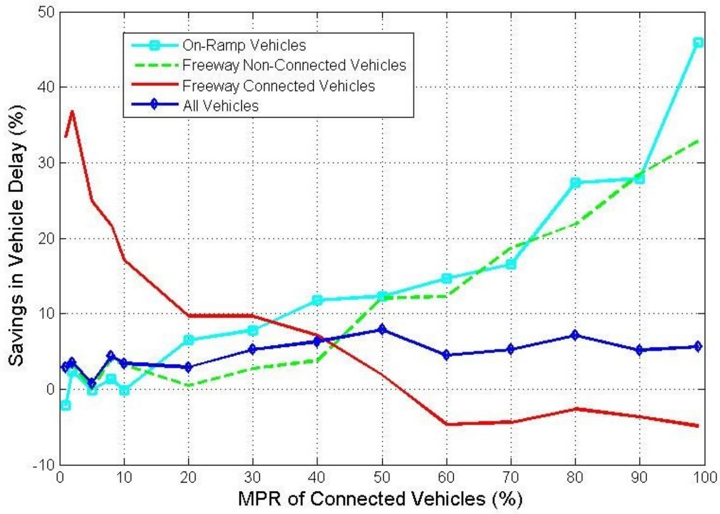
4. System Evaluation

With the sensitivity analysis in the aforementioned section, the optimal values of the system variables are determined as $\mu = 0.94, \beta = 0.07, L = 1000$ m, and $\Delta t = 10$ s. In this section, the incident management system with optimal settings is evaluated under different MPRs of CVs, V/C ratios, and incident status.

4.1. Impact of MPRs

In this subsection, the performance of the incident management system under different CV MPRs is assessed. The simulation setup remains consistent with the previously described section, with the incident occurring on the right two lanes. The CV MPR is varied from 0% to 100% to assess its impact on system performance. Figure 7a shows the savings of average delays of different types of vehicles under different MPRs of CVs. For freeway CVs, the delay savings are more significant at lower market penetration rates (MPRs). However, when the MPR is very high, their performance may deteriorate compared to the base case. This is due to the independent decision making of CVs, where a higher MPR results in more CVs being directed to the left two lanes, leading to increased congestion in those lanes. The maximum delay savings for CVs occur at an MPR of approximately 36%. In contrast, the delay savings for freeway non-CVs, on-ramp vehicles, and all vehicles increase with higher MPRs. These benefits arise from improved traffic conditions across the entire roadway upstream of the incident. At an MPR of 100%, the delay for all vehicles can be reduced by up to 6%, highlighting the potential of full CV deployment to optimize traffic flow.

In the second scenario, the incident is set to occur in the middle two lanes, and all vehicles are instructed to change lanes to either the left-most or right-most lanes in order to bypass the incident. In contrast to the first scenario where all drivers on the blocked lanes only need to change to the left, the drivers in the second scenario have to make a decision about changing lanes to the left or to the right. Without access to incident information, the system will result in unnecessary lane changes, which will further degrade the performance of the entire road network. This inefficient maneuvering can lead to increased congestion and delays, rather than alleviating the problem. Figure 7b summarizes the results in the second scenario. There is a convex relationship between the delay savings of CVs and MPRs. Similar to the first scenario, at higher MPRs, the delay savings for CVs are initially smaller. However, the delay in the second scenario is much higher. At higher MPRs, the performance of the entire road can be significantly improved. Hence, the delay savings of CVs can also be larger at higher MPRs. Moreover, on-ramp vehicles typically use the right-most lane to bypass incidents. However, with the system in place, some CVs are directed to the right lanes, which increases congestion. As a result, the performance of on-ramp vehicles initially worsens. Nonetheless, as the MPR of CVs increases and the system improves the overall road mobility, the delay savings for on-ramp vehicles become positive and grow larger. Similar to the first scenario, at higher MPRs, the delay savings for non-CVs and all vehicles also increase. When all freeway vehicles are controlled at an MPR = 100%, the overall traffic delay can be reduced by up to 47%, significantly alleviating road congestion.



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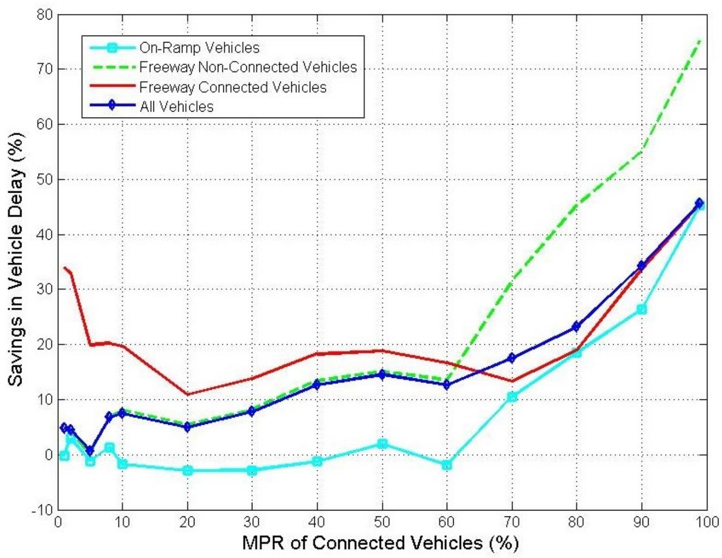


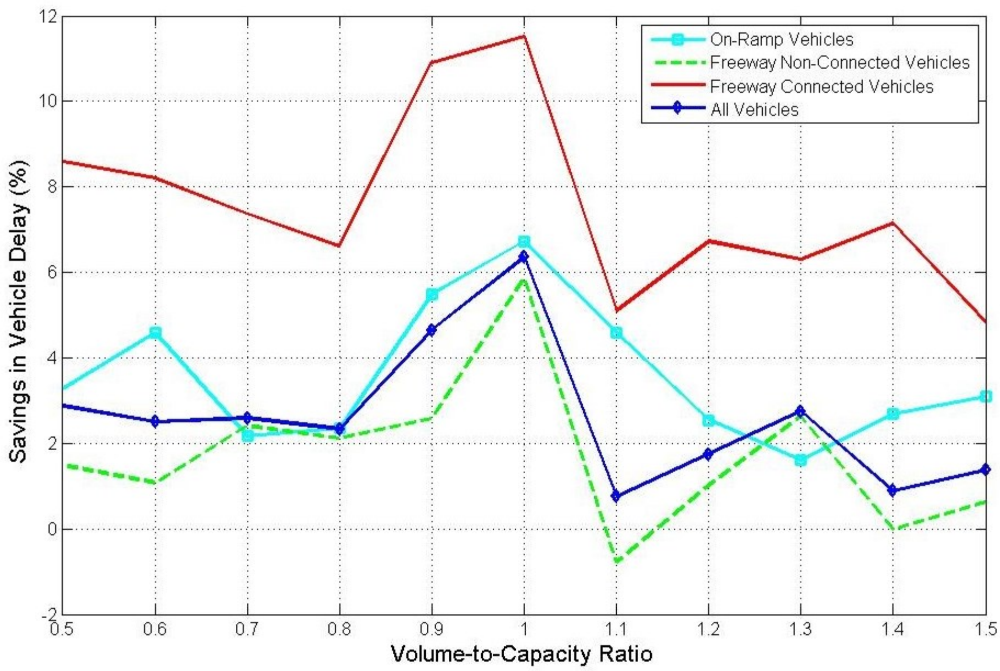
(**b**)

Figure 7. Delay savings under different CV MPRs: (**a**) incident on the right two lanes; (**b**) incident on the middle two lanes.

4.2. Impact of V/C Ratio

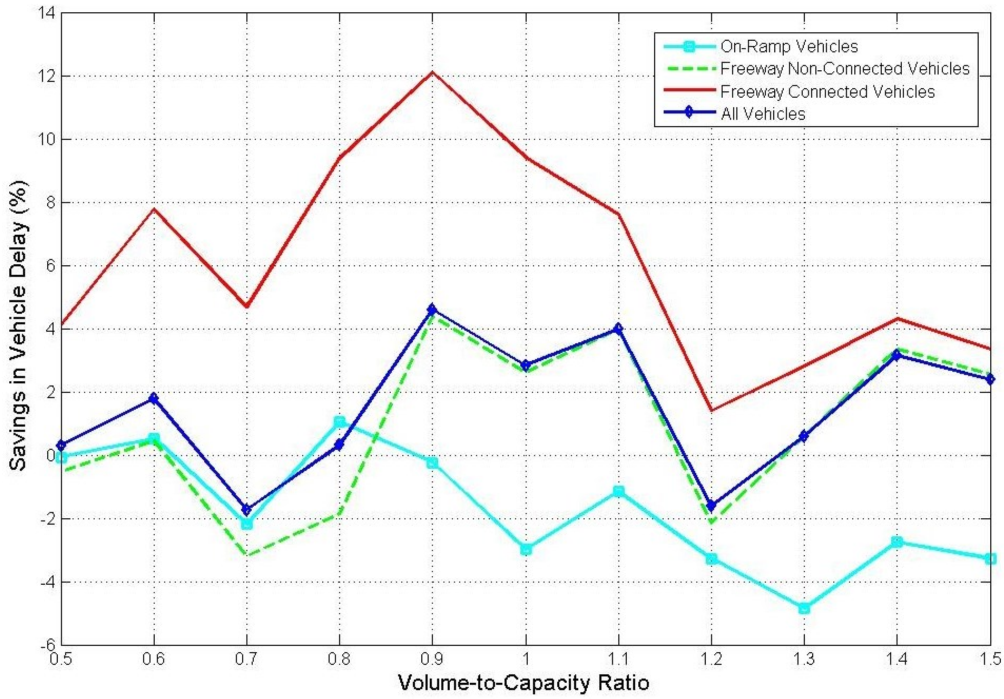
This subsection evaluates the reliability of the incident management system under different congestion levels. The simulation settings are consistent with those from the previous scenario, and two incidents occurring in the right and middle two lanes are simulated to assess how varying levels of congestion affect system performance. The MPR of CVs is set as 20%, and the optimal values of the system variables are applied in these experiments. In addition, the freeway volume-to-capacity (V/C) ratio varies from 0.5 to 1.5.

Figure 8a shows the delay savings under different V/C ratios with an incident on the right two lanes. Clearly, there is an optimal V/C ratio that maximizes the performance of the incident management system. In this scenario, the optimal ratio is 1, where the delay savings for all vehicles exceed 6%, and 11.5% for CVs. For all the other vehicles, their performance is also maximized at the optimal ratio. The result is similar to our expectation based on the mechanism of the system. Under low V/C ratios, the road is not congested, and all vehicles, including both connected and non-CVs, can pass the incident without long delays. At high V/C ratios, the road is too congested, and longer queues will be formed at all lanes. In that sense, even with the optimal lane instruction, the delay reductions cannot be large. The road still has the capacity to release all vehicles with lower delays, but only when the ratio is around 1. Without instructions, vehicles will make unnecessary lane changes, causing intense lane changes close to an incident. In that sense, the capacity drop effect occurs, and the road can become extremely congested. The incident management system, which provides optimal instructions based on the traffic and incident information, is designed to solve this problem. Hence, it has an optimal performance of around 1. Similar results can also be found for the second scenario when the incident occurs on the middle two lanes in Figure 8b. The delay of all vehicles can be reduced by up to 5% with an optimal V/C ratio of 0.9.



(**a**)

Figure 8. *Cont.*



(**b**)

Figure 8. Delay savings under different freeway V/C ratios: (**a**) incident on the right two lanes; (**b**) incident on the middle two lanes.

5. Conclusions

In this paper, we conducted a comprehensive sensitivity analysis of the incident management system to evaluate its effectiveness in mitigating road traffic congestion caused by incidents. The impacts of four parameters, the speed weight factor μ, the lane-changing inertial factor β, the control length L, and the updating interval Δt, were analyzed to search for the optimal system settings in order to maximize its benefit on minimizing travel time delays and mitigating road congestion caused by incidents. In addition, with the optimal parameter settings, the system was also evaluated under different MPRs of CVs, V/C ratios, and incident settings. The results indicated that the system had a better effect on improving CV performance at lower MPRs due to the independent decision making of the vehicle, and all other vehicles could gain higher delay savings at high MPRs due to a congestion reduction caused by the system. Regarding V/C ratios, the system had the best performance when the ratio was close to 1, when it could fully utilize the capacity of the road. Furthermore, this study also indicated that the system can work better at higher MPRs for incidents with a severe impact on road traffic.

In this paper, the proposed incident management system, which is a distributed control system, was evaluated under different parameter settings and traffic scenarios. While effective in many cases, the system has limitations when dealing with high market penetration rates (MPRs) of CVs and severe traffic congestion. To address these challenges, our future work will focus on developing a centralized system capable of simultaneously coordinating all CVs, thereby mitigating the reduced system benefits observed at high MPRs. In addition, the current study primarily examines the mobility benefits of the incident management system without differentiating between vehicle types. However, different vehicles face distinct challenges during congestion, such as range anxiety in electric vehicles (EVs) and the limitations of power grid networks. Our future research will encompass a study in which we will design an integrated vehicle control system that will optimize both mobility and energy efficiency for various vehicle types when navigating road events. This system will aim to balance reduced travel delays and energy conservation, ensuring that CVs and EVs can dynamically respond to incidents while maintaining optimal performance, with considerations for energy storage and management [24,25]. Additionally, the system, currently focused on managing vehicles near incidents, will be integrated with broader traffic control strategies, such as variable speed limits and dynamic routing. This integration will enable more efficient management of a larger number of vehicles affected by incidents across extensive road networks. Furthermore, vehicles often face an increased risk of collisions near road incidents due to sudden speed reductions. Our future study will integrate CVs with automated control systems to enhance both mobility and safety. This will involve precisely managing lateral and longitudinal speeds, enabling vehicles to navigate road incidents more effectively under varying road conditions and geometries. Lastly, the existing model assumes a perfect communication environment free from latency and packet loss. Thus, our future work will explore the impact of communication variability on the system's performance and overall benefits.

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