Longitudinal safety evaluation of connected vehicles’ platooning on expressways

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ABSTRACT

Connected vehicles (CV) technology has recently drawn an increasing attention from governments, vehicle manufacturers, and researchers. One of the biggest issues facing CVs popularization associates it with the market penetration rate (MPR). The full market penetration of CVs might not be accomplished recently. Therefore, traffic flow will likely be composed of a mixture of conventional vehicles and CVs. In this context, the study of CV MPR is worthwhile in the CV transition period. The overarching goal of this study was to evaluate longitudinal safety of CV platoons by comparing the implementation of managed-lane CV platoons and all lanes CV platoons (with same MPR) over non-CV scenario. This study applied the CV concept on a congested expressway (SR408) in Florida to improve traffic safety. The Intelligent Driver Model (IDM) along with the platooning concept were used to regulate the driving behavior of CV platoons with an assumption that the CVs would follow this behavior in real-world. A high-level control algorithm of CVs in a managed-lane was proposed in order to form platoons with three joining strategies: rear join, front join, and cut-in joint. Five surrogate safety measures, standard deviation of speed, time exposed time-to-collision (TET), time integrated time-to-collision (ITT), time exposed rear-end crash risk index (TERCRI), and sideswipe crash risk (SSCR) were utilized as indicators for safety evaluation. The results showed that both CV approaches (i.e., managed-lane CV platoons, and all lanes CV platoons) significantly improved the longitudinal safety in the studied expressway compared to the non-CV scenario. In terms of surrogate safety measures, the managed-lane CV platoons significantly outperformed all lanes CV platoons with the same MPR. Different time-to-collision (TTC) thresholds were also tested and showed similar results on traffic safety. Results of this study provide useful insight for the management of CV MPR as managed-lane CV platoons.

1. Introduction

The development of information and communication technologies have facilitated connected vehicle (CV) technologies, in which vehicles communicate with other vehicles (V2V), roadway infrastructure (V2I), and pedestrians (V2P) in real-time. CV is regarded as one of the most promising methods to improve traffic safety. According to the National Highway Traffic Safety Administration (NHTSA), at a full V2V adoption, CV technology will annually prevent 439,000–615,000 crashes (NHTSA, 2016). Nevertheless, the full market penetration rate (MPR) of CV will not be accomplished recently (NHTSA, 2016). Hence, traffic flow will be a mixture of conventional vehicles and CVs. Some studies have found that the efficiency of CV technologies is heavily decided by the CV MPR (Lee et al., 2013; Paikari et al., 2014; Talebpour and Mahmassani, 2016; Yang et al., 2016). Thus, in the CV transition period, studying the MPR on the safety impact of CV technology is needed.

Vehicle platooning with CV technology is another key element of the future transportation systems which help us to enhance traffic operations and safety simultaneously. Recent research (Tian et al., 2016) proposed a stochastic model to evaluate the collision probability for the heterogeneous vehicle platooning which can deal with the inter-vehicle distance distribution. The results showed great potential in decreasing the chain collisions and alleviating the severity of chain collisions in the platoon at the same time. The platoon-based driving may significantly improve traffic safety and efficiency because a platoon has closer headways and lower speed variations compared to traditional traffic flow. The platoon-based cooperative driving system has been widely studied. However, there have not been enough studies that allocate managed-lane CV platoons which is highly related to CV MPR. The safety benefits of managed-lane CV platoons are expected to be positive because of the dissociation of conventional vehicles and CVs in the

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same lane. Most of the research in CV technology were related to the implementation of CV in all the lanes of the entire roadway with different MPRs. However, until this point, no researcher has potentially analyzed the managed-lane CV platoons which are expected to decrease the crash risk. Fig. 1 illustrates the managed-lane CV concept along with the regular vehicles’ lanes.

The overarching goal of this study was to evaluate the longitudinal safety evaluation of managed-lane CV platoons on a congested expressway. To have better understanding of managed-lane CV effectiveness, this study selected a congested expressway SR408 which has 17 weaving segments. The simulation experiments are first designed, including deployment of both CV platoons as managed-lane and all lanes in this expressway. Then, a driving behavior model for CVs along with the platooning concept were used with an assumption that the CVs would follow this driving behavior in real-world. Five surrogate safety measures, standard deviation of speed, time exposed to-collision (TET), time integrated time-to-collision (TIT), time exposed rear-end crash risk index (TERCR), and sideswipe crash risk (SSCR) were utilized as indicators for safety evaluation. Sensitivity analysis were also conducted for the different time-to-collision (TTC) thresholds. Results of this study provide useful information for expressway safety when CVs are applied as managed-lane concept for the management of CV MPR in the near future.

2. Data preparation

A congested expressway Holland East-West Expressway (SR408) in Orlando, Florida was selected as a testbed for this study. The testbed was a 22-miles section of SR408 with 17 weaving segments from West Colonial Drive, Orlando to Challenger Parkway, Orlando. This expressway is monitored by Microwave Vehicle Detection System (MVDS), and almost all ramps have an MVDS detector to provide ramp traffic information. MVDS indicates the basic traffic characteristics of the selected road segment. The study area along with the MVDS detectors is shown in Fig. 2.

The collected traffic dataset contains seven important variables including volume, speed, and lane occupancy for each lane at 1 min interval, and also categorizes vehicles into four types according to their length; type 1: vehicles 0 to 3 m in length, type 2: vehicles 3–7.5 m in length, type 3: vehicles 7.5–16.5 m in length, type 4: vehicles over 16.5 m in length. In this study, vehicles were classified into two categories: (1) passenger car (PC) and (2) heavy goods vehicle (HGV). A vehicle was considered as a passenger car (PC) if its length is equal to or less than 7.5 m (type 1 and type 2). The traffic data were collected from MVDS detectors installed in the above-mentioned areas (Fig. 2).

3. VISSIM simulation model and calibration

A well calibrated and validated VISSIM network replicating the field condition is the prerequisite of microsimulation based study. Simulations were conducted in PTV VISSIM, version 9.0. The testbed was around 22-miles section of SR 408. The traffic information on the simulation network including, traffic volume aggregated into 5 min intervals, PC and HGV percentages, and desired speed distribution were obtained from the MVDS detectors. The simulation time was set from 6:30 A.M. to 9:30 A.M in VISSIM. After excluding first 30 min of VISSIM warm up time and last 30 min of cool-down time, 180 min VISSIM data was used for calibration and validation. Geoffrey E. Heavers (GEH) statistic was used to compare the field volumes with simulation volumes. The GEH statistic is a modified Chi-square statistic that takes into account both the absolute difference and the percentage difference between the modelled and the observed flows. The definition of GEH is as follows,

$$GEH = \sqrt{\frac{2 \times (M_{obs}(n) - M_{sim}(n))^2}{(M_{obs}(n) + M_{sim}(n))}}$$

(1)

Where $M_{obs}(n)$ is the observed volume from field detectors and $M_{sim}(n)$ is the simulated $M_{obs}(n)$. $M_{sim}(n)/$volume obtained from the simulation network. The simulated volume would precisely reflect the field volume if more than 85% of the measurement locations GEH values are less than five (Wang et al., 2017; Yu and Abdel-Aty, 2014). It is worth mentioning that, for GEH < 5, flows can be considered a good fit; for 5 < GEH < 10, flow may require further investigation; and for 10 < GEH, flow cannot be considered a good fit. To validate the simulation network, average speeds from the field and simulation have been utilized. Mean, minimum, and maximum values of the average speeds from in-field detectors were calculated. As for speed, the absolute speed difference between simulated speeds and field speeds should be within five mph for more than 85% of the checkpoints (Nezamuddin et al., 2011). The simulated traffic volumes and speeds were aggregated to 5 min intervals and then compared with the corresponding field traffic data. Ten simulation runs with different random seeds worth of results showed that 93.23% of observed GEHs were less than five, and 92.92% of the aggregated speeds in the simulation were within five mph of field speeds. The results above proved that the traffic calibration and validation satisfy the requirements, and indicate that the network was consistent with that of the field traffic conditions.

Traffic safety deteriorated significantly in weaving segments compared to non-weaving segments which increase crash risk in weaving segments (Glad, 2001; Golob et al., 2004; Kim and Park, 2016; Pulugurtha and Bhatt, 2010). So, there was a need to revalidate the weaving segment VISSIM network with respect to both traffic and safety. To simplify the further validation process, a sensitivity analysis was conducted on VISSIM driver behavior parameters in simulation models to reflect the weaving segments condition. Based on the literature review, six parameters were chosen for VISSIM calibration and validation for weaving segments (Jolovic and Stefanovic, 2012; Koppula, 2002; Woody, 2006; Wu et al., 2005). They were DLCD (desired lane change distance), CC0 (standstill distance), CC1 (headway time), CC2 (following variation), waiting time per diffusion, and safety distance reduction factor. For each parameter, a range of values (9 values), which includes the default, was determined based on previous study and engineering judgment (Habtemichael and Picado-Santos, 2013). A total of 490 simulation runs (1 base-models + 6 × 8 car-following parameters) times 10 random seeds) were conducted. Toward this end, the standard deviation of speed was selected in order to compare the field and simulated values with two-sample t-test at the 5% significance level. For sensitivity analysis, standard deviation of speed was calculated in 5 min of each run and compared it with the corresponding field standard deviation of speed in 5 min by two sample t-test. For each value of parameters, the results of t-test with 10 different
random seeds proved that the distribution of the field and simulated standard deviation of speeds were identical. The sensitivity analysis results showed that three most important parameters were vital to reflect the safety in weaving segment. These include DLCD, CC1, and safety distance reduction factor. The default value of DLCD, CC1, and safety distance reduction factor in VISSIM were 200 m, 0.9 s, and 0.60, respectively whereas the calibrated values were found to be 400 m, 0.8 s, and 0.50, respectively.

4. Methodology

The overview of whole methodology is expressed in Fig. 3. The CV platoon was deployed in the simulation experiments in a fashion of managed-lane CV platoons and the all lanes CV platoons with same MPR of 40%. For the managed lane simulation experiment, CV platoons were dedicated only in the inner lane (close to the median) and all other lanes were implemented as regular vehicles. While the simulation experiment for all lanes, CV platoons were implemented all the lanes of the expressway along with regular vehicles. The main difference between the base scenario and the all lanes CV platoons was the car following behavior. However, all lanes CV platoons also considered the platooning concept compared to the base scenario. A car following model is a prerequisite to regulate the driving behavior of CVs in microsimulation. In the base scenario, the car following model was used Wiedemann 99 which is the default car following model in VISSIM. Connected vehicles are expected to have the capability of sending/receiving information to/from other vehicles and infrastructure based equipment. In this paper, we considered only the V2V communication using dedicated short-range communication system (DSRC) of 300 m (1000 feet). In reliable connectivity in the vehicle-to-vehicle (V2V) communications networks, each vehicle would receive information about other vehicles in this network. Considering the flow of information in a V2V communications network, drivers are certain about other drivers’ behavior. Moreover, they are aware of the driving environment, road condition, and weather condition downstream of their current location. Therefore, a deterministic acceleration modeling framework is suitable for modeling this environment. Some previous research used the Intelligent Driver Model (IDM) which is proposed by Treiber et al. (2000) in order model this connected vehicle environment (Talebpour et al., 2016, 2015; Talebpour and Mahmassani, 2016). While capturing different congestion dynamics, this model provides greater realism than most of the other deterministic acceleration modeling frameworks. However, only the car following behavior is not enough to model the CV platoons. The platooning technique was also applied by implementing three joining schemes for CVs, such as rear, front, and cut-in joins (see next section for details). The Intelligent Driver Model (IDM) along with the platooning concept were used to regulate the driving behavior of CV platoons with an assumption that the CVs would follow this behavior in the real-world. All the CVs behavior and the control algorithm of the CV platoons will be described in the next section. The outputs of the CV platoons’ behavior model were microscopic simulation traffic data, such as position, speed, occupancy, time interval, vehicle length, and acceleration. Based on surrogate safety measures, a relation can be established between these microscopic data and longitudinal safety.

4.1. CV with platooning behavior model

A car following model is a prerequisite to regulate the driving behavior of CVs in microsimulation. The intelligent driver model (IDM), introduced by Treiber et al. (2000), is a non-linear car following model for which the acceleration ($a_{IDM}$) is calculated by the speed differences ($\Delta v$) and the dynamic desired gap distance ($s^*$). Most
researchers used IDM as machine driving platform in order to simulate their own driving behavior such as adaptive cruise control (ACC) and cooperative adaptive cruise control (CACC) in microsimulation (Kesting et al., 2010, 2008; Khondaker and Kattan, 2015; Li et al., 2017a). The acceleration ($v_{IDM}$) is expressed in Eq. 2 and Eq. 3.

$$\begin{align*}
v_{IDM}(t + t_a) &= \max \left\{ b_{ma}, a_m \left[ 1 - \left( \frac{v}{v_0} \right)^{\delta} - \left( \frac{s}{s_0} \right)^{2} \right] \right\} \\
s^* &= s_0 + \max \left\{ 0, v_T + \frac{v_{d}v}{2a_m\delta} \right\}
\end{align*}$$

(2) (3)

where, $t_a$ = the perception-reaction time, $b_{ma}$ = the maximum deceleration, $a_m$ = the maximum acceleration, $v_0$ = the desired speed, $\delta$ = the acceleration exponent, $s$ = the gap distance between two vehicles, $s_0$ = the minimum gap distance at standstill, $T$ = the safe time headway, and $b$ = the desired deceleration.

The parameters of the IDM model should be calibrated based on the empirical data of CVs which are unavailable. Hence, the parameter calibrations are currently intractable. Nevertheless, all the model parameters of this IDM model were potentially determined according to previous studies (Kesting et al., 2010; Li et al., 2017a, 2017b; Milanés and Shladover, 2014) which were basically modelling with Adaptive Cruise Control (ACC). Other research also used the same parameters value in order to simulate the connected vehicle environment (Talebpour et al., 2015; Talebpour and Mahmassani, 2016). The parameters of CVs behavior model are presented below in Table 1.

Additionally, CVs were implemented as a platooning concept (CVPL), wherein several vehicles form a “platoon” that behaves as a single unit. In this study, three joining schemes for CVs, such as rear, front, and cut-in joins were implemented to maintain the platoon. For managed-lane CV platoons’ scenario, platoons form in the lane dedicated for CV managed lane. While all lanes CV platoons’ scenario, platoons form in any lane of the designated roadway. The joining scheme of CVs in CV manage-lane and all lanes CV scenarios are presented in Figs. 4 and 5, respectively to maintain a platoon. The rear join leads a new CV from regular vehicle lane following the last vehicle of a CV group in a managed lane driving along the most adjacent lane of the joining vehicle (Fig. 4). For the all lanes CV scenario, the rear join leads a new CV following the last vehicle of a CV group in any lane driving along the most adjacent lane of the joining vehicle (Fig. 5). Thus, the joining process is similar between the managed-lane CV platoons and all lanes CV platoons. The only difference is that platooning occurs at the designated managed lane in the managed-lane CV platoons. While the simulation experiment for all lanes, CV platoons were implemented at all the lanes of the expressway along with regular vehicles. The front join performs the same process as rear join to allow a new CV from regular vehicle lane to join into an existing CV group in CV managed lane except that it leads the joining vehicle to the front of the first vehicle in the CV group. The cut-in join method is implemented by cooperatively adjusting the maneuvers of the joining vehicle from regular lane and a CV of managed lane in the group. As shown in Fig. 4, once the joining vehicle identifies a target CV group in the CV managed lane, it approaches the group and determines a proper position to be inserted based on its current driving information such as speed, position, etc. Then the deceleration rate of a CV in the target group is adjusted to create a safe gap for the joining vehicle while the leading vehicle maintains its current speed. If the safe gap is satisfied for the lane change behavior of the joining vehicle, which is governed by VISSIM’s lane changing model, the joining vehicle begins to change the lane.

We developed high-level control algorithm architecture for managed-lane and all lanes CV platoons as shown in Figs. 6 and 7, respectively. The all lanes CV platoon’s scenario is almost the same as the managed lane CV platoon’s scenario. The same car following model (IDM) along with the platooning concept were used in both scenarios to simulate the behavior of CVs. The only difference is that CVs were allowed to occupy all the lanes of the roadway in the all lanes CV platoon’s scenario. Moreover, platooning can form at any lane of the roadway in the all lanes CV platoon. For managed-lane CV platoon’s scenario, CVs were allowed only in the designated managed lane of the roadway. The platoons were also formed in the managed-lane only. It is worth mentioning that the algorithm continuously adjusted the deceleration or deceleration rates using the above-mentioned IDM equation between the leading and the subject vehicles using dedicated short-range communication (DSRC) system of 300 m (1000 feet). The main assumption is that all the CV vehicles will follow the control algorithm in the real-world.

The driving behavior model of CV platoons for both approaches (i.e., managed-lane CV platoons, all lanes CV platoons) were implemented as Dynamic Link Library (DLL) plug-in, which overrides the VISSIM default driving behavior. The DLL were written in C++ which offers VISSIM an option to replace the internal driving behavior and create the V2V communication system. Note that the car following and the lane changing behavior of non-CVs were determined by VISSIM’s default driving behavior model.

The comparison among these three scenarios (base, all lanes CV platoons’, and managed-lane CV platoons’ scenarios) are presented in Table 2.

### Table 1

Model parameter settings.

<table>
<thead>
<tr>
<th>Model Parameters</th>
<th>Connected Vehicle</th>
</tr>
</thead>
<tbody>
<tr>
<td>Desired speed, $v_0$</td>
<td>120 km/h</td>
</tr>
<tr>
<td>Acceleration exponent, $\delta$</td>
<td>4</td>
</tr>
<tr>
<td>Maximum acceleration, $a_m$</td>
<td>1 m/sec$^2$</td>
</tr>
<tr>
<td>Desired deceleration, $b$</td>
<td>2 m/sec$^2$</td>
</tr>
<tr>
<td>Minimum gap distance at standstill, $s_0$</td>
<td>2 m</td>
</tr>
<tr>
<td>Safe time headway, $T$</td>
<td>0.6 sec</td>
</tr>
<tr>
<td>Maximum deceleration, $b_{ma}$</td>
<td>2.8 m/sec$^2$</td>
</tr>
<tr>
<td>Time delay, $t_a$</td>
<td>1.5 sec</td>
</tr>
</tbody>
</table>

### 4.2. Surrogate measures of safety

Traffic crashes are rare events which involve numerous human factors along with the road environment and vehicle factors. A surrogate safety assessment technique should be adopted to measure safety as microsimulation software cannot be directly used to measure crashes or traffic safety. So, the surrogate measures of safety are widely used as proxy indicators to evaluate the crash risk in microsimulation. A number of previous studies used surrogate measures including speed variance, time-to-collision, post-encroachment time, and rear-end crash risk index (Abdel-Aty et al., 2009; Gettman and Head, 2003; Peng et al., 2017). In this study, five surrogate measures of safety were considered to evaluate the traffic safety. Standard deviation of speed was considered one of the surrogate measures of safety. Two surrogate measures of safety, derived from TTC and denoted as time exposed time-to-collision (TET) and time integrated time-to-collision (TIT), are utilized to establish relation between microscopic traffic data and longitudinal safety of CVs.

The TTC is firstly introduced by Hayward, (1972), referring to the time that remains until a collision between the leading and following vehicles will occur if the speed difference is maintained. To be more specific, the TTC represents the time required for two successive vehicles, occupying the same lane, to collide if they continue at their present speed when vehicle $n$ moves faster than the preceding vehicle ($n - 1$). The TTC notion can be expressed as Eq. 4:
dangerous traffic conditions, determined by $TTC_{\text{brake}}$ value below the threshold value of TTC ($TTC^*$).

$$TTC_n(t) = \begin{cases} \frac{x_{n-1}(t) - x_n(t) - L_{n-1}}{v_n(t)}, & \text{if } v_n(t) > v_{n-1}(t) \\ \infty, & \text{if } v_n(t) \leq v_{n-1}(t) \end{cases} \quad (4)$$

where $TTC_n(t)$ is the TTC value of vehicle $n$ at time $t$, $x$ is the positions of vehicles, $v = L_{n-1}$

$TTC_n(t)$ x/the velocities of vehicles, $L_{n-1}$ = Length of preceding vehicles.

Furthermore, two types of TTC are usually utilized in traffic safety analysis: TTC1 and TTC2. TTC1 assumes the preceding vehicle maintains its speed, while TTC2 describes situations when the preceding vehicle stops suddenly, which is also called TTC at braking (Peng et al., 2017). During the simulation, traffic data was collected at eighteen detectors in the VISSIM network, and few small TTC1 was observed during the simulation. Thus, TTC at braking (TTC2) is employed in this study to evaluate traffic safety in different situations. In this study, the definition of the TTC at braking ($TTC_{\text{brake}}$) is as follows (Peng et al., 2017):

$$TTC_{\text{brake}}(t) = \frac{x_{n-1}(t) - x_n(t) - L_{n-1}}{v_n(t)} \quad (5)$$

The smaller $TTC_{\text{brake}}$ value indicates the larger risk at a certain time instant. The TET and TIT, two aggregate indicators developed by Minderhoud and Bovy, (2001), are potentially used in this study as surrogate safety measures. The TET refers to the total time spent under

$$TET(t) = \sum_{n=1}^{N} \delta_i \times \Delta t, \quad \delta_i = \begin{cases} 1, & 0 < TTC_{\text{brake}}(t) \leq TTC^* \\ 0, & \text{otherwise} \end{cases} \quad (6)$$

$$TET = \sum_{t=1}^{\text{Time}} TET(t) \quad (7)$$

where $t$ = the time ID, $n$ = the vehicle ID, $N$ = the total number of vehicles, $\delta$ = the switching variable, $\Delta t$ = the time step, which was 0.1 s in simulation, Time = the simulation period, and $TTC^*$ = the threshold of TTC. The $TTC^*$ is used to differentiate the unsafe car following conditions from ones considered safe. According to previous studies, the values of $TTC^*$ varies from 1 to 3 s (Li et al., 2016, 2014; Sultan et al., 2002).

The TIT notion refers to the entity of the $TTC_{\text{brake}}$ lower than the threshold. The reciprocal transformation was made considering that a lower TTC means a higher collision risk:

$$TIT(t) = \sum_{n=1}^{N} \left( \frac{1}{TTC_{\text{brake}}(t)} - \frac{1}{TTC^*} \right) \Delta t, \quad 0 < TTC_{\text{brake}}(t) \leq TTC^* \quad (8)$$
Additionally, rear end crashes are the most common type of crashes in any roadway. A rear-end crash may occur if the leading vehicle stops suddenly, and the following vehicle does not decelerate in time. So, maintaining insufficient safety distance between the leading and the following vehicle is the primary cause of rear-end crashes. To avoid the rear-end crashes, the stopping distance of the following vehicle should be smaller than the leading vehicle. A rear-end crash risk index (RCRI) proposed by Oh et al. (Oh et al., 2006) in which the dangerous condition can be mathematically expressed as:

\[ SD_F > SD_L \]  \hspace{1cm} (10)

\[ SD_L = \frac{v_L^2}{2a_L} + l_L \]  \hspace{1cm} (11)

\[ SD_F = v_F \times PRT + \frac{v_F^2}{2a_F} \]  \hspace{1cm} (12)

Where \( SD_L \) and \( SD_F \) are the stopping distance of the leading and the following vehicles, respectively. \( l_L \) the length of the leading vehicle, \( v_L \) the speed of the leading vehicle, \( v_F \) the speed of the following vehicle, \( PRT \) is the perception-reaction time, \( h \) the time headway, \( a_L \) the deceleration rate of the leading vehicle and \( a_F \) is the deceleration rate of the following vehicle. As mentioned earlier, for the VISSIM model, we used two types of vehicles PC and HGV. Therefore, different deceleration rates were employed to estimate the reliable safe distance for the leading and following vehicles. The deceleration rates of PC and HGV were selected as 3.42 m/s² and 2.42 m/s² respectively, while the PRT was used as 1.5 s, these values are generally accepted by AASHTO (American Association of State Highway and Transportation Officials (AASHTO), 2004). We proposed one surrogate measures of safety, derived from RCRI and denoted as time exposed rear-end crash risk index (TERCRI).

\[ TERCRI (t) = \sum_{n=1}^{N} \text{RCRI}_L (t) \times \Delta t, \quad \text{RCRI}_L (t) = \begin{cases} 1, & \text{SDF} > \text{SDL} \\ 0, & \text{Otherwise} \end{cases} \]  \hspace{1cm} (13)
Fig. 8. Standard deviation of speed, TET, TIT, TERCRI, and SSCR distribution with different scenarios.

Table 3
Summary statistics of standard deviation of speed, TET, TIT, TERCRI, and SSCR.

<table>
<thead>
<tr>
<th>Scenarios</th>
<th>Measures</th>
<th>Number of Runs</th>
<th>Minimum</th>
<th>Maximum</th>
<th>Mean</th>
<th>Standard Deviation</th>
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<tr>
<td>Base</td>
<td>SD of speed (%)</td>
<td>20</td>
<td>13.04</td>
<td>15.83</td>
<td>14.26</td>
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<tr>
<td></td>
<td>TET (s)</td>
<td>20</td>
<td>4482</td>
<td>4692</td>
<td>4569.45</td>
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<td></td>
<td>TIT (s)</td>
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<td>2440</td>
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<td></td>
<td>TERCRI (s)</td>
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<td>2881</td>
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<tr>
<td></td>
<td>SSCR</td>
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<td>1310</td>
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<td>All lane CV</td>
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<td>11.98</td>
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<td>CV managed lane</td>
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<td>TERCRI (s)</td>
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<td>1947</td>
<td>2036</td>
<td>1984.25</td>
<td>24.77</td>
</tr>
<tr>
<td></td>
<td>SSCR</td>
<td>20</td>
<td>538</td>
<td>612</td>
<td>564.95</td>
<td>22.37</td>
</tr>
</tbody>
</table>

*a Sd of speed = standard deviation of speed.*
sideswipe crash occurs during the lane changing maneuver. However, it is worth mentioning that the most common way of a sideswipe crash occurs during the lane changing maneuver. However, it can also happen in a lane changing maneuver on ramps. Therefore, the lane changing conflict can be a surrogate measure of the sideswipe crash risk (SSCR). It is difficult to find out the surrogate measures of sideswipe crashes analytically. Therefore, the Surrogate Safety Assessment Model (SSAM) (Gettman et al. (2008)), developed by the Federal Highway Administration, was applied to analyze the lane changing conflict which can be related to the surrogate measures of the sideswipe crashes. The experimental VISSIM model generated several groups of traffic trajectory data files. The vehicle conflicts’ data were stored in these trajectory data files which, contains the conflict locations’ coordinates, conflict time, time-to-conflict, and post-encroachment-time among other measures. Hence, the SSAM was applied to analyze these conflict data in order to compare the SSCR among the three scenarios.

In a nutshell, the standard deviation of speed, TET, TIT, TERCRI, and SSCR were considered as surrogate measures of safety in order to evaluate the longitudinal safety of managed-lane CV platoons.

5. Results and discussions

Five surrogate measures of safety were considered to evaluate the safety performances of managed-lane CV platoons in an expressway. To have a better understanding, we introduced CV platoons in all the lanes and only in a managed-lane on the expressway with similar MPR. These two CV scenarios were compared with the base scenario (non-CV scenario) in order to observe the effectiveness of CV platoons. As mentioned earlier standard deviation of speed, TET, TIT, TERCRI, and SSCR are the five surrogate measures of safety considered in this study. Each scenario (base scenario, all lanes CV platoons, managed-lane CV platoons) was repeatedly simulated for 20 times in order to consider random effects of simulation and the preliminary results are shown in Fig. 8. The TTC threshold was considered 2 s for the preliminary analysis and then a sensitivity analysis is conducted for different TTC thresholds from 1 to 3 s.

As shown in Fig. 8, the distribution of standard deviation of speed, TET, TIT, TERCRI, and SSCR of each scenario approximately followed the normal distribution because of the random effect of simulation. However, the magnitudes (minimum value, maximum value) were significantly different for each scenario. The values (minimum, maximum) of standard deviation of speed, TET, TIT, TERCRI, and SSCR of base scenario were found to be ranged between [12, 16], [4400, 4725], [2175, 2475], [2700, 2925], and [1212, 1310] respectively.

The descriptive statistics of standard deviation of speed, TET, TIT, TERCRI, and SSCR in three scenarios are presented in Table 3. The non-CV scenario has the largest mean value of each standard deviation of speed, 3601.15 of TET, 1857.90 of TIT, 2249.00 of TERCRI, and 751.30 of SSCR, respectively.

While the five indicators of all lanes CV platoons’ scenario were within approximately [12, 14], [3485, 3725], [1725, 1970], [2125, 2375], and [712, 787] respectively and the scenario with managed-lane CV platoons were within approximately [10.75, 11.5], [3250, 3450], [1600, 1775], [1910, 2060], and [538, 612] respectively. The larger values of each surrogate safety indicator imply the more dangerous situations. Hence, there are the higher longitudinal crash risks in base scenario compared to managed-lane CV platoons and all lane CV platoons. Among the three scenarios, all five indicators had the lowest values for managed-lane CV platoons representing a safer situation.

The descriptive statistics of standard deviation of speed, TET, TIT, TERCRI, and SSCR in three scenarios are presented in Table 3. The non-CV scenario has the largest mean value of each standard deviation of speed (14.26), TET (4569.45), TIT (2333.05), TERCRI (2807.40), and SSCR (1263.80) followed by the all lanes CV platoons with 12.91 of standard deviation of speed, 3601.15 of TET, 1857.90 of TIT, 2249.00 of TERCRI, and 751.30 of SSCR, respectively.

The mean value of five surrogate indicators of managed-lane CV platoons were lowest with mean standard deviation of speed (11.12), TET (3345.60), TIT (1688.10), TERCRI (1984.25), and SSCR (564.95), respectively. Therefore, the scenario with managed-lane CV platoons has the lowest longitudinal crash risks compared to all lanes CV platoon, while the scenario with base condition has the highest crash risk.

The One-way ANOVA analysis are also presented in Table 4 which indicates significant differences among these three scenarios and infer that managed-lane CV platoons significantly outperformed all lane CV platoon.

A heat map is also represented in Fig. 9 which shows the effectiveness of managed-lane CV platoons and all lanes CV platoon over non-CV scenario. Managed-lane CV platoons has the highest safety improvement in terms of five surrogate measures of safety presented in heat map. In managed-lane CV platoons’ scenario, the values of standard deviation of speed, TET, TIT, TERCRI, and SSCR were lowest with lighter color in heat map.

On the other hand, the values of five surrogate measures of safety

![Table 4](https://example.com/table4.png)

**Table 4**

One-way ANOVA analysis of standard deviation of speed, TET, TIT, TERCRI, and SSCR.

<table>
<thead>
<tr>
<th>Measures</th>
<th>Attribute</th>
<th>Sum of squares</th>
<th>DF</th>
<th>Mean Squares</th>
<th>F-value</th>
<th>Significance</th>
</tr>
</thead>
<tbody>
<tr>
<td>Standard deviation of Speed (km/h)</td>
<td>Between</td>
<td>99.32</td>
<td>2</td>
<td>49.66</td>
<td>188.33</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td></td>
<td>Groups</td>
<td>15.03</td>
<td>57</td>
<td>0.26</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Within Groups</td>
<td>114.35</td>
<td>59</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TET (s)</td>
<td>Between</td>
<td>16,671,463.43</td>
<td>2</td>
<td>8335731.72</td>
<td>4486.73</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td></td>
<td>Groups</td>
<td>105898.30</td>
<td>57</td>
<td>1857.86</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Within Groups</td>
<td>16777361.73</td>
<td>59</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>TIT (s)</td>
<td>Between</td>
<td>4,470,400.43</td>
<td>2</td>
<td>2235200.22</td>
<td>1345.16</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td></td>
<td>Groups</td>
<td>94714.55</td>
<td>57</td>
<td>1661.66</td>
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<td></td>
</tr>
<tr>
<td></td>
<td>Within Groups</td>
<td>4565114.98</td>
<td>59</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>TERCRI (s)</td>
<td>Between</td>
<td>7,063,193.63</td>
<td>2</td>
<td>3531596.82</td>
<td>2738.25</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td></td>
<td>Groups</td>
<td>73514.55</td>
<td>57</td>
<td>1289.73</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>Within Groups</td>
<td>7136708.18</td>
<td>59</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Total</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>SSCR</td>
<td>Between</td>
<td>5,238,492.63</td>
<td>2</td>
<td>2619246.32</td>
<td>5133.24</td>
<td>&lt; 0.0001</td>
</tr>
<tr>
<td></td>
<td>Groups</td>
<td>29084.35</td>
<td>57</td>
<td>510.25</td>
<td></td>
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</tr>
<tr>
<td></td>
<td>Within Groups</td>
<td>5267576.98</td>
<td>59</td>
<td></td>
<td></td>
<td></td>
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<tr>
<td>Total</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

TERCRI = \( \sum_{t=1}^{T} \text{TERCRI}(t) \) (14)
Fig. 9. Heat map of surrogate measures of safety.

Table 5
Sensitivity analysis of different values of TTC threshold.

<table>
<thead>
<tr>
<th>TTC (s)</th>
<th>Scenarios</th>
<th>Base condition</th>
<th>Scenario 1 (All lane CV)</th>
<th>Scenario 2 (Managed-lane CV)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Measures</td>
<td>TET</td>
<td>TIT</td>
<td>TET</td>
</tr>
<tr>
<td>1.0</td>
<td>Average</td>
<td>2238</td>
<td>674</td>
<td>1765</td>
</tr>
<tr>
<td></td>
<td>proportion</td>
<td>–</td>
<td>–</td>
<td>21%</td>
</tr>
<tr>
<td>1.5</td>
<td>Average</td>
<td>3634</td>
<td>1654</td>
<td>2921</td>
</tr>
<tr>
<td></td>
<td>proportion</td>
<td>–</td>
<td>–</td>
<td>19%</td>
</tr>
<tr>
<td>2.0</td>
<td>Average</td>
<td>4569</td>
<td>2333</td>
<td>3601</td>
</tr>
<tr>
<td></td>
<td>proportion</td>
<td>–</td>
<td>–</td>
<td>21%</td>
</tr>
<tr>
<td>2.5</td>
<td>Average</td>
<td>5290</td>
<td>2824</td>
<td>4222</td>
</tr>
<tr>
<td></td>
<td>proportion</td>
<td>–</td>
<td>–</td>
<td>20%</td>
</tr>
<tr>
<td>3.0</td>
<td>Average</td>
<td>5889</td>
<td>3205</td>
<td>4634</td>
</tr>
<tr>
<td></td>
<td>proportion</td>
<td>–</td>
<td>–</td>
<td>21%</td>
</tr>
</tbody>
</table>
were largest representing higher crash risk in non-CV scenario with most darker color. In all lanes CV platoons’ scenario, the values of aforementioned surrogate measures of safety are smaller than base scenario but larger than the managed-lane CV platoons’ scenario. From the above discussion, it is inferred that managed-lane CV platoons clearly outperformed the all lanes CV platoons in terms of surrogate measures of safety.

The above results of TET and TIT are mainly based on the same parameter setting of TTC threshold is 2 s. Sensitivity analysis of TTC thresholds were also conducted. The various values TTC threshold do not affect the results of simulations. The five values of TTC threshold ranging from 1 to 3 s have almost same results which is presented in Table 5. Compared with base scenario, all the reductions of TIT and TET values maintain within 19% to 21% for all lanes CV platoons with different values of TTC threshold. And the TIT and TET values are all reduced within 26%–28% of managed-lane CV platoons compared with that of base condition.

Overall, the deployment of CV platoon of all lanes and managed-lane in studied congested expressway would significantly decrease the standard deviation of speed, TET, TIT, TERCRI, and SSCR; thereby might decrease the probability of crashes. But, it is clearly seen that managed-lane CV platoons significantly outperformed all lanes CV platoons with same MPR.

6. Conclusion

The primary objective of this study was to evaluate longitudinal safety of managed-lane CV platoons on expressways based on simulation results. The simulation experiments were designed, by deploying managed-lane CV platoons and all lanes CV platoons on a congested expressway. Then, a vehicle behavior model for CV platoon was used based on the IDM model and five surrogate safety measures, standard deviation of speed, TET, TIT, TERCRI, and SSCR were measured as safety indicators. Sensitivity analysis were also conducted for different TTC thresholds to compare the results among the three scenarios.

The distribution of five surrogate measures of safety approximately follow the normal distribution because of the stochastic nature of simulation. The values of standard deviation of speed, TET, TIT, TERCRI, and SSCR were largest for the base (non-CV) scenario. The results showed that both CV platoons scenarios improved safety significantly over non-CV scenario. However, the surrogate safety measures were smaller in managed lane CV platoons compared to all lanes CV platoons. Hence, traffic stream with managed-lane CV platoons has lower longitudinal crash risks compared to all lanes CV platoons. One-way ANOVA analysis showed significant differences among the three tested scenarios and inferred that managed-lane CV platoons significantly outperformed all lanes CV platoons. And, the results of sensitivity analysis indicated that the TTC threshold ranging from 1 to 3 s have almost the same results. Hence, the different TTC thresholds did not affect the simulation results.

From our analysis, it is evident that managed lane CV platoons and all lanes CV platoons significantly improved the longitudinal safety in the studied expressway segments compared to the base condition. In terms of surrogate safety measures, the managed-lane CV platoons significantly outperformed all lanes CV platoons with the same MPR. The study is not without limitations. In our research effort, we considered several IDM parameters that were implemented in previous studies. The parameters should be calibrated based on the empirical data of CVs which are unavailable, thus parameter calibrations are currently intractable. However, the optimization of these parameters was out of the scope for this study. This study can be a good platform for further analysis with a combination of variable speed limit, ramp metering, and CV technology in any congested expressway.

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Washington, DC.


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