Understanding the Highway Safety Benefits of Different Approaches of Connected Vehicles in Reduced Visibility Conditions

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Abstract
This study evaluated the effectiveness of connected vehicle (CV) technologies in adverse visibility conditions using microscopic traffic simulation. Traffic flow characteristics deteriorate significantly in reduced visibility conditions resulting in high crash risks. This study applied CV technologies on a segment of Interstate I-4 in Florida to improve traffic safety under fog conditions. Two types of CV approaches (i.e., connected vehicles without platooning (CVWPL) and connected vehicles with platooning (CVPL) were applied to reduce the crash risk in terms of three surrogate measures of safety: the standard deviation of speed, the standard deviation of headway, and rear-end crash risk index (RCRI). This study implemented vehicle-to-vehicle (V2V) communication technologies of CVs to acquire real-time traffic data using the microsimulation software VISSIM. A car-following model for both CV approaches was used with an assumption that the CVs would follow this car-following behavior in fog conditions. The model performances were evaluated under different CV market penetration rates (MPRs). The results showed that both CV approaches improved safety significantly in fog conditions as MPRs increase. To be more specific, the minimum MPR should be 30% to provide significant safety benefits in terms of surrogate measures of safety for both CV approaches over the base scenario (non-CV scenario). In terms of surrogate safety measures, CVPL significantly outperformed CVWPL when MPRs were equal to or higher than 50%. The results also indicated a significant improvement in the traffic operation characteristics in terms of average speed.

It is known that reduced visibility due to fog has caused serious traffic safety and flow issues. Florida had experienced a total of 4,954 fog-related crashes between the year of 2008 and 2012, of which 132 crashes were fatal, and about 30% of the total fog-related crashes were fatal and injury crashes (1). It is worth mentioning that fog-related crashes tend to result in more severe injuries and involve more vehicles compared with clear conditions crashes (2, 3). Fog affects roadway safety by increasing crash risk. Therefore, it is necessary to evaluate the appropriate countermeasures to enhance traffic safety under fog conditions.

There has already been a lot of research conducted on traffic safety under normal weather conditions. On the other hand, traffic safety under fog conditions has attracted much less attention. However, some researchers have already proposed the traditional approach of variable speed limits (VSL) or variable message signs (VMS) to decrease the crash risk in reduced visibility conditions (1, 3, 4). This approach can possibly improve traffic safety and mitigate traffic crashes by adjusting vehicle speeds and decreasing speed variation among vehicles in reduced visibility conditions. Nevertheless, the success of VSL or VMS is dependent on the level of compliance (5–7). Therefore, the VSL would not guarantee the improvement of traffic safety if drivers do not follow the new speed limit.

An innovative feature of this study was to apply the connected vehicle (CV) technologies in adverse visibility conditions under a microsimulation environment. To be more specific, this research aims to contribute to the implementation of two CV approaches, that is,
connected vehicle without platooning (CVWPL) and connected vehicle with platooning (CVPL), to improve traffic safety in reduced visibility conditions. CVPL concept is an extension of CVWPL approach in which several CVs form a “platoon” that behaves as a single unit. A car-following model for both CV approaches was also used in fog conditions with an assumption that applied CVs would follow this car-following behavior in the simulation. The most significant difference of CVs driving behavior between the two approaches was joining vehicles to maintain a platoon. In the near future, the market penetration rate (MPR) will not achieve 100%. Meanwhile, the penetration will increase gradually. Hence, it is worthwhile to study the safety benefits of CV technologies under different MPRs.

Background

Florida is among the highest ranked states in the United States with regards to traffic safety problems resulting from adverse weather conditions, especially in fog. As an example, a fog-related severe crash caused 5 fatalities, several injuries, and left a pileup of 70 vehicles on I-4, Polk County, Florida (4). The injury and death rates (per 100 crashes) for fog-related crashes and were found to be 3.75 and 2.25 for the corresponding type of crashes occurring in normal weather conditions, respectively (8). Previous studies have been examined to evaluate the traffic characteristics in fog conditions. Abdel-Aty et al. (9) conducted a comprehensive study with an effort to examine the traffic characteristics in fog conditions. The study concluded that speed and headway decreased significantly under reduced visibility conditions. Furthermore, the standard deviation of speed and headway increased in fog conditions compared to clear conditions. A more recent study by Peng et al. (1) identified that reduced visibility would significantly increase the standard deviation of speed and headway which intensifies traffic crash risk. It was also observed that time to collision decreased significantly in reduced visibility conditions, which means that the crash risk would be higher under reduced visibility conditions. They also found that the impact of low visibility on crash risk was different for different vehicle types and for different lanes. The crash risk is higher for passenger vehicles compared with heavy vehicles, and the inner lane (close to the median) has higher crash risk compared with the middle and outer lanes. Other studies also pointed out that headway distance was reduced in fog conditions and sometimes reduced headway would have a perceptual control benefit to the driver in terms of reduction in response time under fog conditions (10, 11). Brooks et al. (12) examined the effect of fog conditions on lane-keeping ability using driving simulator. It was shown that lane keeping performances were significantly degraded by the existence of fog.

There is relatively little work in the literature describing the countermeasures in reduced visibility conditions. The findings of the previous studies provided several recommendations as guidelines to improve safety in reduced visibility conditions. Based on a questionnaire survey, Hassan et al. (4) suggested that changeable message signs can be a good countermeasure to reduce driving speed. Pang et al. (13) used a simulation-based study to examine traffic safety and operation in fog conditions. The study showed that fog-related crashes were reduced by controlling upstream traffic flow (decreasing upstream traffic volume) and implementing VSL. Peng et al. (1) suggested that implementing the algorithms in real-time with intelligent transport system (ITS) measures, such as VSL and VMS, can reduce the crash risk in reduced visibility conditions. Speed variance would be lower with the implementation of VSL, which in turn decrease crash risk (14–17). In terms of safety, VSL has been used during inclement weather to decrease both the mean and the standard deviation of speed (18, 19). However, the success of the VSL application is more dependent on the compliance level. In the low level of compliance, the VSL might fail to improve traffic safety (5–7). The research by Abdel-Aty et al. (15) also evaluated that the implementation of VSL might reduce the rear-end and lane-change crash risks in uncongested traffic conditions but not successfully reduce the crash risk in congested situations. Therefore, the success of the VSL is also dependent on the level of congestion.

The new ITS technology, CV, has been recently recognized as an auspicious approach which proved its potential to improve traffic safety, including mitigating crash severity and declining the possibility of crashes by offering vehicle to vehicle (V2V) and vehicle to infrastructure (V2I) communication. Most of the previous research was concerned with the mobility and the traffic operations under CV environment but did not focus on traffic safety. Fyfe and Sayed (20) combined VISSIM and the surrogate safety assessment model (SSAM) with the application of the cumulative travel time (CTT) algorithm which evaluates the safety under CV environment. The study showed a 40% reduction of rear-end conflict frequency at a signalized intersection with the application of CV. Olia et al. (21) experimented with CV technology in PARAMICS and estimated that the safety index improved up to 45% under CV environment. Paikari et al. (22) also used PARAMICS which combined the V2V and V2I technologies and obtained higher safety and mobility enhancement on freeways under the CV environment. Vehicle platooning with CV technology is another key element of future transportation systems which helps to enhance traffic operations and safety simultaneously. Tian et al. (23) proposed a stochastic model to evaluate the collision probability for the
heterogeneous vehicle platoon which can deal with the intervehicle distance distribution. The results have great potential to decrease chain collisions and alleviate the severity of chain collisions in the platoon at the same time. However, until this point, no researcher has potentially analyzed CV technologies which are expected to decrease the crash risk in reduced visibility conditions.

When compared with the previous studies, this study is unique in a sense that it reflects the fog conditions in microscopic simulation and applies CV technologies which are expected to improve traffic safety in reduced visibility conditions.

Data Preparation

A section of Interstate, a main arterial for the Orlando metropolitan area, was selected for this study. The studied section had experienced severe fog-related crashes (3). Data from two different sources were collected for this study. Weather data were collected from Fog Monitoring System (FMS), a new visibility detection system, installed in the segment of I-4. And, real-time traffic data were collected from Regional Integrated Transportation Information System (RITIS) augmented with a device installed close to the FMS. RITIS indicates the basic traffic characteristics of the selected road segment, while the added device captures both regular traffic parameters and the headway between each vehicle on each lane.

The collected weather data contain 21 variables, including visibility distance, air temperature, surface moisture, dew point, wind speed, barometric pressure, rainfall, and so forth. Among these parameters, visibility distance is significant for fog conditions. The traffic data were collected from RITIS detectors. The traffic dataset comprises eight important variables related to traffic flow characteristics, including vehicle speed, vehicle length, duration of detection, and lane assignment. 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 PC if its length was equal to or less than 7.32 m (24 ft). According to the weather data, the visibility distance from 6:45 a.m. to 7:45 a.m. on February 2, 2016 (Tuesday) was the lowest among all days of field data collection between the observed months of January to May in 2016. And this hour’s maximum and minimum visibility distance were recorded as 88 m and 45 m, respectively. Referring to the traffic flow data, the data of traffic volume and traffic speed in the same period, 6:45 a.m. to 7:45 a.m. on February 2, were chosen for basic simulation model development.

VISSIM Simulation Model

A well calibrated and validated VISSIM network replicating the fog conditions was one of the most important parts of this study. Simulations were conducted in PTV VISSIM, version 8.0. The testbed was a 10-mile section of I-4 which had experienced a severe fog-related crash. The traffic information on the simulation network, including traffic volume (aggregated into 15 min), PC and HGV percentages, and desired speed distribution were obtained from the RITIS detectors. In addition to that, the “Look Ahead Distance” was changed in VISSIM driving behavior to replicate reduced visibility conditions based on field visibility distance. The simulation time was set from 6:15 a.m. to 8:15 a.m. in VISSIM. After excluding first 30 min of VISSIM warmup time and last 30 min of cooldown time (no statistics were collected during this time), 60 min of 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 incorporates both relative and absolute differences. The definition of GEH is

\[ \text{GEH} = \sqrt{\frac{(M_{\text{obs}}(n) - M_{\text{sim}}(n))^2}{0.5 \times (M_{\text{obs}}(n) + M_{\text{sim}}(n))}} \]  

where \( M_{\text{obs}}(n) \) is the observed volume of field detectors and \( M_{\text{sim}}(n) \) is the simulated 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 5 (5, 24). As for speed, the absolute speed difference between simulated speeds and field speeds should be within 5 mph for more than 85% of the checkpoints (25). The simulated traffic volumes and speeds were aggregated to 15-min intervals and then compared with the corresponding field traffic data. Ten simulation runs with different random seeds worth of results showed that 91.25% of observed GEHs were less than 5, and 92.50% of the aggregated speeds in the simulation were within 5 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.

Further Calibration to Reflect Fog Conditions

To reflect the fog conditions, there was a need to revalidate the VISSIM network with respect to both traffic and safety. For further validation, headway was used to validate the VISSIM network using two-sample t-test and the result showed that the mean simulated headway was significantly different from the mean field headway when all the driver behavior parameters in VISSIM were set as default. Previous studies considered only “Look Ahead Distance” as one of the most essential simulation parameters in VISSIM to replicate the fog conditions (26, 27). Hence,
changing only the “Look Ahead Distance” in VISSIM driving behavior may not reflect the fog conditions. To simplify the further calibration process, a sensitivity analysis was conducted on VISSIM driver behavior parameters in simulation models to reflect the fog conditions. The 10 sets of the car-following parameters (CC0 to CC9) were tried and each set was run 10 times with different random seeds. For each parameter, a range of values (9 values), which includes the default, was determined based on previous studies and engineering judgment (28, 29). A total of 730 simulation runs ([1 base-models + 9 × 8 car-following parameters] times 10 random seeds) were conducted. Toward this end, the standard deviation of speed (significant traffic characteristic in fog condition) was selected to compare the field and simulated value with two-sample t-test at 5% significance level. For each value of parameters, the results of t-test with 10 different random seeds proved whether the distribution of the field and simulated standard deviation of speed were identical or not. The sensitivity analysis results showed that three most important parameters were vital to reflect the fog conditions. These were CC0 (standstill distance), CC1 (headway time), and CC2 (following variation). From the results of sensitivity analysis, the safety distance parameters (i.e. CC0, CC1, CC2) decreased compared to the default values in fog conditions. The default value of CC0, CC1, CC2 in VISSIM were 1.5 m, 0.9 sec, and 4 m whereas the calibrated values were found to be 1 m, 0.7 sec, and 3 m, respectively. Thus, the safety distance of the calibrated network has lower value compared to the uncalibrated network. Therefore, the safety distance between two vehicles has been reduced in fog conditions. For further validation, headway was again used to validate the new calibrated VISSIM network using two-sample t-test. After replicating the fog conditions, there was no significant difference between the simulated mean headway and the field mean headway. Therefore, the simulation network was well calibrated and validated with respect to both traffic and safety.

**Methodologies**

To assess the safety performance in fog conditions, this paper tested two distinct CV approaches including CVWPL and CVPL on the segment of I-4. Therefore, the understanding of the car-following behavior of CV technologies is essential for studying the impact on traffic safety in fog conditions under microsimulation. A car-following model for both CV approaches was used in fog conditions with an assumption that applied CVs would follow this car-following behavior in the simulation.

**Car-Following Model in Fog Conditions**

A car-following model is a prerequisite to regulate the driving behavior of CVs in microsimulation. The desired model should be able to simulate user defined driving behavior significantly differing from the traditional ones (i.e. Wiedemann model). The basic Intelligent Driver Model (IDM) which was proposed by Treiber et al. (30) has been used as machine driving by many researchers (31, 32). Many researchers have already used IDM or modified IDM in order to simulate their own machine driving platform named Adaptive Cruise Control (ACC) and Cooperative Adaptive Cruise Control (CACC) (31, 32). The basic IDM model is a nonlinear car-following model in which the acceleration (\(v_{IDM}\)) is the function of desired gap distance \(s^*\) and the speed difference between leading and following vehicles \(\Delta v\), expressed by

\[
v_{IDM}(t + t_a) = \max \left \{ b_m, a_m \left [ 1 - \left ( \frac{v}{v_0} \right )^\delta - \left ( \frac{s^*}{s} \right )^2 \right ] \right \} \text{ (2)}
\]

where

\(s^* = s_0 + \max \left [ 0, vT - \frac{v_0}{2v_0a_m} \right ]\)

and

\(t_a = \text{perception-reaction time},\)

\(b_m = \text{maximum deceleration},\)

\(a_m = \text{maximum acceleration},\)

\(v = \text{speed of the following vehicle},\)

\(v_0 = \text{desired speed},\)

\(\delta = \text{acceleration exponent},\)

\(s = \text{gap distance between two vehicles},\)

\(s_0 = \text{minimum gap distance at standstill},\)

\(T = \text{the safe time headway, and}\)

\(b = \text{the desired deceleration}\)

In this study, this IDM model was used for CVs car-following behavior in fog conditions. The parameter settings for this model were potentially determined according to previous studies (31–33). The desired speed \(v_0\), acceleration exponent \(\delta\), maximum acceleration \(a_m\), desired deceleration \(b\), minimum gap distance at standstill \(s_0\), safe time headway \(T\), maximum deceleration \(b_m\), and time delay \(t_a\) were selected 120 km/h, 4, 1 m/sec\(^2\), 2 m/sec\(^2\), 2 m, 0.6 sec, 2.8 m/sec\(^2\), and 1.5 sec, respectively.

Additionally, CVs were implemented as a platooning concept (CVPL), in which several vehicles form a “platoon” that behaves as a single unit. However, the IDM model was followed by CVs in both approaches (i.e., CVWPL and CVPL) under fog conditions. The most significant difference of CVs driving behavior between the two approaches was joining vehicles to maintain a platoon. A minimum five CVs were considered to maintain a platoon in this study. Three grouping schemes for CVs, such as rear, front, and cut-in joins, as depicted in Figure 1, were implemented to maintain the platoon. The rear join leads a new CV following the last vehicle of a CV group driving along the most adjacent lane of the joining vehicle. The front join performs the same
process to allow a new CV to join into an existing CV group 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 and a CV in the group. As shown in Figure 1, once the joining vehicle identifies a target CV group, it approaches the group and determines a proper position to be inserted based on its current driving information such as speed, position, and so forth. 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 lane.

A high-level control algorithm architecture was developed for CVPL approach as shown in Figure 2. It is worth mentioning that the algorithm continuously adjusted the acceleration or deceleration rates using the above-mentioned Equation 2 between the leading and the subject vehicles using two-way communications under CV environment which offers a dedicated short-range communication (DSRC) of 300 m (1000 ft).

The aforementioned two driving behavior models were implemented as dynamic link library (DLL) plug-in for both approaches, which overrides the VISSIM default driving behavior. These two DLL were written in C++ which offers VISSIM an option to replace the internal driving behavior. During the simulation, the DLL file is called up in each time step and then controls the behavior of the vehicle for all or part of the vehicles depending on the MPRs. Note that the car-following and the lane-changing behavior of non-CVs were determined by VISSIM’s default driving behavior model.

**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. A number of previous studies used surrogate measures including speed variance, headway variance, time to collision, post-encroachment time, and RCRI \( (1, 15, 34) \). From the above-mentioned literature review the crash risk increased in fog conditions compared to normal weather conditions as the standard deviation of speed and headway increased significantly. Additionally, the rear-end crash is the significant type of crash in reduced visibility conditions \( (2, 8, 35) \). A rear-end crash may occur if the leading vehicle stops suddenly, and the following vehicle does not decelerate in time because of the low visibility. Maintaining insufficient safety distance between the leading and the following vehicle is the primary cause of rear-end crashes. To avoid the rear-end crash the stopping distance of the following vehicle should be smaller than the leading vehicle. An RCRI is proposed by Oh et al. \( (36) \) in which the dangerous condition can be mathematically expressed as
\[ SD_L = v_L \times h + \frac{v_L^2}{2 \times a_L} + l_L \]
\[ SD_F = v_F \times PRT + \frac{v_F^2}{2 \times a_F} \]

where

- \( SD_L \) = stopping distance of the leading vehicle,
- \( SD_F \) = stopping distance of the following vehicle,
- \( l_L \) = length of the leading vehicle,
- \( v_L \) = speed of the leading vehicle,
- \( v_F \) = speed of the following vehicle,
- \( PRT \) = perception–reaction time,
- \( h \) = time headway,
- \( a_L \) = deceleration rate of the leading vehicle, and
- \( a_F \) = deceleration rate of the following vehicle.

As mentioned earlier, for the VISSIM model, two types of vehicles were used: 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/s\(^2\) and 2.42 m/s\(^2\) respectively, while the PRT was used as 1.5 s. These values are generally accepted by AASHTO (37). So, the RCRI is defined by the formula

\[ RCRI = \begin{cases} 
1 & \text{(Dangerous) If } SDF > SD_L \\
0 & \text{(Safe) Otherwise}
\end{cases} \]
performances were evaluated for three different condition sets (Base, CVWPL and CVPL) each under five different MPRs (20%, 30%, 50%, 70%, and 100%). To find out the safety impact of the applied technologies the mean values of the surrogate safety measures were compared with the base condition. In 100% MPR, the standard deviation of speed and the standard deviation of headway were found to be reduced by 28.49% and 18.68%, respectively, in CVWPL compared to base condition. On the other hand, in CVPL, the reductions were found to be 38.90% and 33.22%, respectively. The results revealed that the applied CV technologies enhanced traffic safety by decreasing the surrogate measures of safety in fog conditions. From Table 1 it was found that the maximum significant improvement resulted at 100% MPR, while the improvement below 30% MPRs was insignificant at 5% level of significance.

For each of the 15 scenarios listed in Table 1, the mean differences of standard deviation of speed and standard deviation of headway were higher for CVPL than CVWPL. It was also found that the CVPL achieved significant reductions in the standard deviation of speed and headway compared to CVWPL when the MPRs were equal or greater than 50%. For instance, standard deviation of speed and standard deviation of headway for CVPL were 0.174# (0.2503) and 0.948# (0.0001) respectively, while these values were 0.134# (0.0001) and 0.812# (0.0001) respectively, in CVWPL compared to base condition. On the other hand, in CVPL, the reductions were found to be 38.90% and 33.22%, respectively. The results revealed that the applied CV technologies enhanced traffic safety by decreasing the surrogate measures of safety in fog conditions. From Table 1 it was found that the maximum significant improvement resulted at 100% MPR, while the improvement below 30% MPRs was insignificant at 5% level of significance.

Additionally, compared to CVWPL, the average speed was higher in CVPL. Hence, for both traffic safety and operation the CVPL approach outperformed CVWPL approach.

Figure 3 shows the decreasing trend of standard deviation of speed and headway for CVWPL and CVPL approaches with increasing MPRs. As seen from the figure, the higher the percentage of the CVs implemented, the lower were the standard deviations of speed and headway, and therefore the higher were the safety benefits achieved.

Apart from statistical significance, Figure 4a and b compares the profile of both the surrogate measures of safety under base, CVWPL and CVPL scenario in 100% MPR. For every 2-min time interval which is denoted in the x axis, the standard deviation of speed and standard deviation of headway (denoted in y axis) were calculated. Figure 4a and b illustrates that both CV approaches not only reduced the standard deviation of speed and headway but were able also to stabilize the profile. With lower variances in standard deviation of speed and headway these CV technologies are expected to decrease the crash risks.

The RCRI was considered as another surrogate measure for rear-end crashes. The Chi-square test was applied to test the significance in differences of RCRI between base scenario and CV scenarios. The percentages of vehicles under potential rear-end crash risk for different scenarios are listed in Table 2 with the Chi-square significance test. It can be seen from Table 2 that the percentages of potential rear-end crash observations were

### Table 1. Summary of Measure of Effectiveness

<table>
<thead>
<tr>
<th>MPR</th>
<th>Comparisons</th>
<th>Speed (km/h)</th>
<th>Standard deviation of speed in 2 mins (km/h)</th>
<th>Standard deviation of headway in 2 mins (s)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Mean difference (P-value)</td>
<td>Mean difference (P-value)</td>
<td>% Reduction</td>
</tr>
<tr>
<td>20%</td>
<td>Base vs CVWPL</td>
<td>−0.288 (0.0322)</td>
<td>0.264# (0.1915)</td>
<td>2.78</td>
</tr>
<tr>
<td></td>
<td>Base vs CVPL</td>
<td>−0.398 (0.0030)</td>
<td>0.375# (0.0642)</td>
<td>3.96</td>
</tr>
<tr>
<td></td>
<td>CVWPL vs CVPL</td>
<td>−0.108# (0.4062)</td>
<td>0.111# (0.4997)</td>
<td>1.20</td>
</tr>
<tr>
<td>30%</td>
<td>Base vs CVWPL</td>
<td>−0.570 (&lt;0.0001)</td>
<td>0.597 (0.0042)</td>
<td>6.29</td>
</tr>
<tr>
<td></td>
<td>Base vs CVPL</td>
<td>−1.149 (&lt;0.0001)</td>
<td>0.769 (0.0002)</td>
<td>8.12</td>
</tr>
<tr>
<td></td>
<td>CVWPL vs CVPL</td>
<td>−0.579 (&lt;0.0001)</td>
<td>0.174# (0.2503)</td>
<td>1.96</td>
</tr>
<tr>
<td>50%</td>
<td>Base vs CVWPL</td>
<td>−1.334 (&lt;0.0001)</td>
<td>0.848 (&lt;0.0001)</td>
<td>8.95</td>
</tr>
<tr>
<td></td>
<td>Base vs CVPL</td>
<td>−2.457 (&lt;0.0001)</td>
<td>1.476 (&lt;0.0001)</td>
<td>15.57</td>
</tr>
<tr>
<td></td>
<td>CVWPL vs CVPL</td>
<td>−1.125 (&lt;0.0001)</td>
<td>0.626 (0.0005)</td>
<td>7.25</td>
</tr>
<tr>
<td>70%</td>
<td>Base vs CVWPL</td>
<td>−2.395 (&lt;0.0001)</td>
<td>1.745 (&lt;0.0001)</td>
<td>18.41</td>
</tr>
<tr>
<td></td>
<td>Base vs CVPL</td>
<td>−3.275 (&lt;0.0001)</td>
<td>2.536 (&lt;0.0001)</td>
<td>26.76</td>
</tr>
<tr>
<td></td>
<td>CVWPL vs CVPL</td>
<td>−0.880 (&lt;0.0001)</td>
<td>0.793 (&lt;0.0001)</td>
<td>10.24</td>
</tr>
<tr>
<td>100%</td>
<td>Base vs CVWPL</td>
<td>−4.897 (&lt;0.0001)</td>
<td>2.700 (&lt;0.0001)</td>
<td>28.49</td>
</tr>
<tr>
<td></td>
<td>Base vs CVPL</td>
<td>−5.535 (&lt;0.0001)</td>
<td>3.687 (&lt;0.0001)</td>
<td>38.90</td>
</tr>
<tr>
<td></td>
<td>CVWPL vs CVPL</td>
<td>−0.637 (&lt;0.0001)</td>
<td>0.988 (&lt;0.0001)</td>
<td>14.58</td>
</tr>
</tbody>
</table>

*Note: #Difference is insignificant at the 5% level.*
lower for CVWPL and CVPL than the base condition. At 100% MPR, the percentage of vehicles with potential rear-end crash risks were 11.55% lower in CVWPL and 14.67% lower in CVPL compared to the base condition. Hence, the rear-end crash risk decreased with the application of CV technologies. Also, the CVPL approach performed better than the CVWPL approach for each MPR in terms of RCRI. It was also found that at least 30%
MPR was needed to have significant reduction in rear-end crash risk. Additionally, CVPL achieved higher reductions of RCRI compared to CVWPL when the MPRs were equal or greater than 50%. It is worth mentioning that, the higher the MPRs implemented, the lower were the potential rear-end crash observations, and therefore the higher were the safety benefits achieved.

Overall, the deployment of CVs in reduced visibility conditions would significantly decrease the standard deviation of speed, standard deviation of headway, and RCRI; thereby might decrease the probability of crashes.

**Conclusion**

Traffic flow characteristics deteriorate significantly in fog conditions compared to normal weather conditions which might result in high crash risk. In order to improve traffic safety in fog conditions, two CV strategies were applied in microsimulation. The strategies include CVWPL and CVPL. A car-following model for both approaches was used with an assumption that the CVs would follow this car-following behavior in fog conditions. Three surrogate measures of safety including the standard deviation of speed, standard deviation of headway, and RCRI; thereby might decrease the probability of crashes.

<table>
<thead>
<tr>
<th>MPR</th>
<th>Classification</th>
<th>Total observation</th>
<th>Number of potential rear-end crash observation</th>
<th>Comparison</th>
<th>Chi-square</th>
<th>P-value</th>
</tr>
</thead>
<tbody>
<tr>
<td>20%</td>
<td>Base</td>
<td>10035</td>
<td>4161 (41.46%)</td>
<td>Base vs CVWPL</td>
<td>0.780#</td>
<td>0.3770</td>
</tr>
<tr>
<td></td>
<td>CVWPL</td>
<td>10034</td>
<td>4099 (40.85%)</td>
<td>Base vs CVPL</td>
<td>3.274#</td>
<td>0.0704</td>
</tr>
<tr>
<td></td>
<td>CVPL</td>
<td>10035</td>
<td>4035 (40.21%)</td>
<td>CVWPL vs CVPL</td>
<td>0.858#</td>
<td>0.3544</td>
</tr>
<tr>
<td>30%</td>
<td>Base</td>
<td>10035</td>
<td>4161 (41.46%)</td>
<td>Base vs CVWPL</td>
<td>23.487</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>CVWPL</td>
<td>10037</td>
<td>3823 (38.12%)</td>
<td>Base vs CVPL</td>
<td>39.848</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>CVPL</td>
<td>10030</td>
<td>3725 (37.11%)</td>
<td>CVWPL vs CVPL</td>
<td>2.151#</td>
<td>0.1425</td>
</tr>
<tr>
<td>50%</td>
<td>Base</td>
<td>10035</td>
<td>4161 (41.46%)</td>
<td>Base vs CVWPL</td>
<td>75.775</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>CVWPL</td>
<td>10035</td>
<td>3561 (35.49%)</td>
<td>Base vs CVPL</td>
<td>118.091</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>CVPL</td>
<td>10035</td>
<td>3414 (34.03%)</td>
<td>CVWPL vs CVPL</td>
<td>4.704</td>
<td>0.0301</td>
</tr>
<tr>
<td>70%</td>
<td>Base</td>
<td>10035</td>
<td>4161 (41.46%)</td>
<td>Base vs CVWPL</td>
<td>169.646</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>CVWPL</td>
<td>10035</td>
<td>3270 (32.59%)</td>
<td>Base vs CVPL</td>
<td>264.023</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>CVPL</td>
<td>10031</td>
<td>3055 (30.46%)</td>
<td>CVWPL vs CVPL</td>
<td>10.548</td>
<td>0.0012</td>
</tr>
<tr>
<td>100%</td>
<td>Base</td>
<td>10035</td>
<td>4161 (41.46%)</td>
<td>Base vs CVWPL</td>
<td>291.941</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>CVWPL</td>
<td>10040</td>
<td>3003 (29.91%)</td>
<td>Base vs CVPL</td>
<td>480.641</td>
<td>&lt;0.0001</td>
</tr>
<tr>
<td></td>
<td>CVPL</td>
<td>10037</td>
<td>2689 (26.79%)</td>
<td>CVWPL vs CVPL</td>
<td>24.045</td>
<td>&lt;0.0001</td>
</tr>
</tbody>
</table>

Note: #Difference is insignificant at the 5% level.

For the car-following model, this study considered several parameters implemented in previous studies. 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 VSL and CV technologies. In this regard, V2I protocol might be useful with a combination of V2V communication under CV environment.

As a follow-up study, a full-scale field experiment may be considered. Nevertheless, the experiment will be limited for several reasons. First of all, the effects of CV by market penetration rate (MPR) were tested in this...
study. Nevertheless, the full market penetration of CVs will not be accomplished in the near future. Thus, it is difficult to incorporate the effective full-scale field experiment with V2V communication. A full-scale field experiment with a small group of experimental cars with V2V communication might be needed to substantiate and extend the results of this simulation study. That would be very important to policy makers or researchers working toward the implementation of CV technologies.

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Author Contributions

The authors confirm contribution to the paper as follows: study conception and design: Md Sharikur Rahman, Mohamed Abdel-Aty, Ling Wang; data collection: Md Sharikur Rahman; analysis and interpretation of results: Md Sharikur Rahman, Mohamed Abdel-Aty, Ling Wang, Jaeyoung Lee; draft manuscript preparation: Md Sharikur Rahman, Mohamed Abdel-Aty, Ling Wang, Jaeyoung Lee. All authors reviewed the results and approved the final version of the manuscript.

References


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