REAL-TIME CRASH PREDICTION MODEL FOR CRASH RISK EVALUATION DURING DEPLOYMENT OF AUTOMATED VEHICLES

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Successful implementation of automated vehicle (AV) technology can be done by proper safety evaluation which in the future will be required for informative decision-making during large scale deployment of automated vehicles (AVs). The focus of this paper is two folds: understanding appropriate parameter setting for automated vehicle by examining the behavioral models of preceding studies, and later focusing on the introduction of the real-time crash prediction model (RTCPM) based crash risk evaluation using Dynamic Bayesian Network (DBN). After reviewing preceding studies and two large scale real-world projects: CoEXist Project and UK Autodrive, parameters were set by considering three driving environments- normal, cautions, and all-knowing. For the study parameters from CoEXist Project were used for the analysis due to its accessibility. DBN based analysis showed that crash risk can be reduced by 11.1%, 13.1%, and 10.6% under normal driving, cautious, all-knowing driving behaviors respectively with mixed scenarios. Results exhibited that with higher market penetration rates, some of the driving volatility measures were reduced such as less lane changing, maintaining homogeneous speed and headways. Also, more cautious behavior of AV, maintaining safe gap and safe time headway, contributes to a greater benefit on traffic safety by reducing crash risk.

Key Words : *Dynamic Bayesian Network, Real-Time Crash Prediction, Automated Vehicle, Driving behavior, Crash risk evaluation*

1. INTRODUCTION

Recently, introducing automated or autonomous vehicles (AVs) or connected and autonomous vehicle (CAV) in automated driving system (ADS) has become a worldwide hot-topic. Implementation of AVs on the road network has increased partly due to their ability to reduce the number of crashes caused by the human errors. Different studies showed that the number of conflicts can be reduced from 12%-94% with the 25%-100% market penetration rates (MPRs) of AVs (Jeong et al., 2017; Morando et al., 2018; Papadoulis et al., 2019; Khashayarfard and Nassiri, 2021; Zhang et al., 2021).

According to Zhu and Tasic (2021) the increase of AV penetration rate, the number of conflicts reduced steadily and at 100% penetration rate the probability of near-crashes is reduced to zero. They also showed that the probability of critical merging events (near-crashes and conflicts) is reduced by 13.74% when all human-driven vehicles are replaced by AVs. While Zhu and Tasic (2021) found the reduction of conflicts with increased MPR of AV, Sinha et al. (2020b) showed potential collision rate between autonomous vehicle and human driven vehicle increases with increasing connected and autonomous vehicle (CAV) penetration where crash rate increases from 60% MPR and most critical situation occurred with 70% CAV penetration rate. At 90% CAV penetration the probability of a collision is higher. But at 100 % CAV scenario crash rate is zero which also indicates that full-scale benefits of CAVs can only be achieved at 100 % CAV penetration which is also remain unchanged in their another study, Sinha et al. (2020a). Their results also indicate that safety benefits of CAVs are not proportional to CAV penetration, and by setting appropriate parameter, safe network with minimum collision rate can be achieved with certain

MPR. Guériau et al. (2016) found traffic instabilities with low penetration of AV which can create a more heterogeneous traffic which is responsible for safety reduction. With the increase of MPR of from 20% to 100% cooperative traffic behavior and less lane changes appear which lead to a homogeneous traffic flow with homogeneous speeds and headways, and with homogeneous traffic, traffic safety can be achieved (Guériau et al., 2016). By implementing CAVs for different study areas Virdi et al. (2019) showed that at 20% penetration rate conflicts increases at the signalized and diverging diamond interchange (DDI) intersection by 22% and 33% respectively, whereas decreases at the priority intersection and roundabout by 87% and 62% respectively. A 90% CAV penetration can reduce conflicts by 48%, 100%, 98%, and 81% for the signalized, priority, roundabout and DDI intersection respectively (Virdi et al., 2019). While Papadoulis et al. (2019) found conflicts reduction by 12–47%, 50–80%, 82–92%, and 90–94% for 25%, 50%, 75% and 100% CAV penetration rates respectively, Jeong et al. (2017) observed no clear improvement in traffic safety using the traffic safety-based maneuvering (TSM) parameters with MPRs of less than 50%. TSM parameters were more effective for reducing traffic conflicts at MPRs greater than 75%.

The common limitation of preceding studies was the appropriate parameter setting for AV or CAV due to unavailability of empirical data which also limits the generalization of penetration rate. Sinha et al. (2020b) used parameters collected from naturalistic driving studies which may alter in CAV deployed environment. Their study failed to understand unprecedented crash causes because the CAV characteristics they used for simulation are different from real CAVs which they also face in another study (Sinha et al. (2020a)). On the other hand, Zhu and Tasic (2021) used hypothetical parameters for very high automation level of AV which actually can be only applicable for developing base scenario. Hypothetical parameter and behavior settings, derivation of risk evaluation measure from theoretical perspective lead to bias into the results. Virdi et al. (2019) in their study used 0.5 m headway which seems to be inappropriate in a mixed scenario because the human driven vehicles drive with a headway significantly higher than CAV. The difference in the fundamental behavior of these vehicle types disrupts the order and uniformity of the flow.

Furthermore, most of the studies used surrogate safety measures (SSMs) to estimate the conflicts. Though SSMs have several benefits but they have also some crucial drawbacks. The major disadvantage is that they cannot identify real crash condition, only the hypothetical near-conflict situation. Because of limited AV data, there is limitation in model calibration and validation which can lead to the biased results (partial or inaccurate observation and limited sample size). And in simulation-based SSM, simulated vehicles follow certain preprogrammed paths which can generate biased SSM results. Results can differ with the change of algorithm, threshold values of parameters and so on (Arun et al., 2021; Sohrabi et al., 2021).

This study focuses on the two major aspects: firstly, we discuss appropriate parameters for AV by understanding the behaviorial models and analytical results of previous studies; secondly, we introduce the real-time crash prediction model (RTCPM) instead of SSMs for evaluating the crash risk under different automated vehicle penetration rates. A part of the Shinjuku Route 4 (13.5 km) of the Tokyo Metropolitan Expressway was selected as the study route. Large number of crash cases and relatively uniformly spaced detectors, make it one of the most sophisticatedly instrumented urban expressways in the world. Shinjuku Route 4 is connected to the Chuo Expressway starting at the point on the boundary of the Tokyo Metropolitan area. This expressway has two lanes in each direction with 74 detectors (almost 250 m apart) in each lane (Roy et al., 2022).

2. PRECEDING STUDIES

(1) Driving Behaviorial Models and Parameter Setting for AV

This section mainly focused on the review of most commonly used driving behaviorial models and parameter setting for AV based on preceding studies. Researchers used several models to determine the driving behavior of AV among which most commonly used models are Intelligent Driver Model (IDM) (Rahman et al., 2019; Zhang et al., 2021; Rahman and Abdel-Aty, 2018), Wiedemann 74 or Wiedemann 99 car following behavior model (Khashayarfard and Nassiri, 2021; Morando et al., 2018; Abdel-Aty et al., 2020); and Adaptive Cruise Control (ACC) and Cooperative ACC (CACC) models (Yao et al., 2020; Arvin et al., 2020; Yang et al., 2022). Along with these three models researchers also used different user defined models using different external coding interface (Jeong et al., 2017; Papadoulis et al., 2019; Sinha et al., 2020a, b; Virdi et al., 2019; Ye and Yamamoto, 2019). Figure 1 represents an overview of driving behavior models and parameter setting for AV.

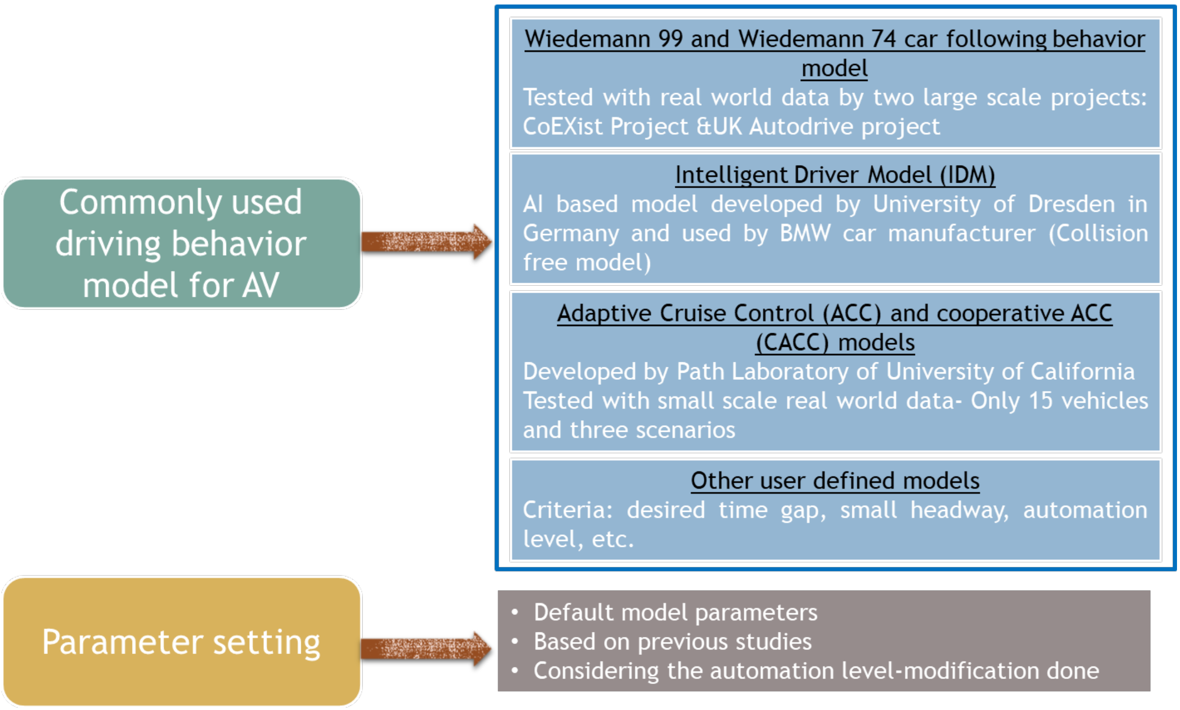

Fig.1 Overview of most commonly used driving behavior models and parameter setting for AV

The intelligent Driver Model (IDM) is the simplest time-continuous theoretical car-following model developed based on the assumption that it would fit very well under both free flow and congested flow (Zhang et al., 2021). According to Kesting et al. (2010) and Treiber and Kesting (2013) IDM has the ability to model oscillations, stop-and-go traffic, and start and stop of a vehicle platoon between two traffic lights by producing realistic accelerations and braking decelerations profile. But IDM has drawbacks: first, during emergency braking deceleration value exceeds the real vehicle value in case of critical situations such as crashes, second, the estimated desired minimum gap is not enough to guarantee driver safety, and the third drawback is that the IDM is considered a collision-free model. For example, in the case of an emergency braking scenario, the IDM can generate a non-realistic deceleration to avoid collision (Derbel et al., 2013). Furthermore, due to lack of empirical data, values of parameters were difficult to calibrate (Rahman et al., 2019; Zhang et al., 2021) and for this reason values and parameters were set based on different previous studies. For example, Rahman et al. (2019) determined IDM parameters according to previous studies conducted by Rahman et al. (2018) and Rahman and Abdel-Aty (2018).

On the other hand, Wiedemann is a psychophysical car-following model developed by Wiedemann in 1974. In this model the main goal of the following car is to avoid collision with the leader vehicle while aiming to maintain the desired speed if conditions prevail. However, the speed may become smaller than the lead vehicle speed as the results of driver's imperfection in the estimation of the lead vehicle speed. This means the driver will accelerate slightly again after reaching another threshold. This results in an iterative process of acceleration and deceleration due to drivers' imperfections in the exact speeds of the lead vehicles. In some traffic simulators such as VISSIM, two types of the model were adopted : Wiedemann74 and Wiedemann99 where Wiedemann74 is suggested to be applied for urban arterial roads and the other one is more suitable for freeways (VISSIM, 2021; Rahal et al., 2017). In VISSIM, these models were already calibrated and validated using real-world AV data in the CoEXist project, which is a well-known project launched in May 2017 funded by many organizations including PTV, Renault, and several universities in the Europe (Sukennik, 2018; Khashayarfard and Nassiri, 2021). In the next section, the parameter setting of this model in detail is discussed.

Automated vehicles with ACC can capture the speed and acceleration information of the front vehicle through the monitoring equipment installed on the vehicle, while the CACC can obtain the driving information based on the vehicle-to-vehicle communication equipment (Yao et al., 2020). Both ACC and CACC car following models were developed and validated based on the real-world AV data (Milanés and Shladover, 2014). Though these parameters were tested with real world data but the sample size was very small- only 15 vehicles and three scenarios were considered: ten-vehicle CACC scenario; five-vehicle ACC scenario; and scenario with mixture of CACC-equipped and ACC-equipped vehicles (Milanés and

Shladover, 2014).

Finally, different user defined models were used to evaluate the characteristics of automated vehicles. All these models were developed based on different criteria of automated vehicles including, desired time gap, small headway, automation level, throttle control and breaking behavior, platoon formation concept, etc. Researchers defined parameters mainly based on the headway gap and automation level. Virdi et al. (2019) and Sinha et al. (2020a) defined critical headway gap as 0.5 meter for the automation level 4 or 5. On the other hand, Papadoulis et al. (2019) in their study used shorter headway time 0.6s and also considered that connected autonomous vehicles would have the same throttle control and breaking behavior as conventional vehicles. Zhu and Tasic (2021) used Monte-Carlo method where they used hypothetical parameters for defining driving behavior of AVs. Sinha et al. (2020b) in their another study also considered short headway, 0.5 meter, and used user defined model where they considered standstill distance, inter-platooning spacing, maximum allowed acceleration, and maximum allowed deceleration 0.5 m, 30 m, 6 m/s2, and -8 m/s2.

(2) Wiedmann 99 Car-following Model in VISSIM

Car-following model in the VISSIM software was built based on four driving logics for AV: rail safe, cautious, normal, and all-knowing driving logics. Rail safe driving logic has a deterministic behavior, which fits quite well to automatically moving machineries especially in closed environments of ports or factory where in cautious driving logic, drivers always respect the road code and safe behavior. On the other hand, normal driving logic (driving behavior is almost like human driver) focuses on the capability of measuring speeds and gaps with the surrounding vehicles with their sensors while all-knowing driving logic predicts all other road users' behavior with vehicle-to-vehicle (V2V) or vehicle-to-infrastructure (V2I) technologies (Sukennik, 2018; Abdel-Aty et al., 2020). According to Papadoulis et al. (2019) Wiedemann 99 driving model could contribute to a more accurate safety-orientated calibration of the baseline model as it contained more adjustable driving behavior parameters. Some researchers used recommended parameters (Khashayarfard and Nassiri, 2021; Morando et al., 2018; Abdel-Aty et al., 2020) of Wiedemann99 model by VISSIM estimated from CoExist project. Khashayarfard and Nassiri (2021) also used values from UK Autodrive project, which was adopted by European companies in December 2014 to differentiate driving behavior with PTV CoExist project. Khashayarfard and Nassiri (2021) found total reduction in collisions for UK Auto drive project is higher than CoExist project. We discuss these two projects briefly in the following sections.

(3) CoEXist Project and UK Autodrive Project

"CoEXist Project" has been launched in May 2017 with the involvement of many organizations, including PTV, Renault, and several universities. The project has been put into operation in four cities: Milton, England; Stuttgart, Germany; Helmond, the Netherlands; and Gothenburg, Sweden by considering eight cases. The driving behavior parameter for AVs was set based on the four driving logics that were defined and used within the CoExist project. Value estimation and all recommendations were made based on the analysis of empirical data collected from three AVs that were operated by TASS international in Helmond test track, Netherlands.

Empirical data, from 28th August 2017 to 1st September 2017, were collected in real traffic environment with real automated vehicles in common traffic. Several driving scenarios were incorporated with 3 test vehicles. These vehicles were based on a Toyota Prius 3rd generation. Data collected by this system was filtered based on user defined classification which consisted of original object ID, unique object ID, and classification age and reference point location. Overall thirty scenarios were tested with the different test parameters and their variations. After data collection and processing, several results were obtained which were simulated and validated in VISSIM first, and later VISSIM simulation was tested using VEDECOM's driving control logic. In the first step, the test vehicles had been simulated by using different features and adjusting the parameters of the Wiedemann model. In the second step, deviations from the behavior of the test vehicles were identified and adjustments of the acceleration behavior were made. In the final step, comparison was made with the adjusted driving behavior again to the empirical data for evaluating the results. After having the successful evaluation of all data, the parameters for automated vehicles along with human driven vehicles and values of those parameters had been proposed which were represented in the Table 1.

On the other hand, UK Autodrive project was formed in December 2014 and began with the aim of introducing driverless cars to the UK Transport Network. Many companies were involved in the project, the most important of which were Ford, Jaguar Land Rover, Tata Motors European Technical Center, the University of Cambridge, and University of Oxford. The real-world demonstration of the project was conducted on selected public roads, a mix of grid-based streets and more traditional urban road layouts, in the host cities of Milton Keynes and Coventry. 'Regular' passenger vehicles (M1 classification) equipped with advanced autonomous and connected vehicle communication systems provided by Jaguar Land Rover, Ford Motor Company and Tata Motors European Technical Centre were used for the project. A total of seven M1 cars took part in the program. These vehicles employed a range of sensor, communication and positioning technologies. In total, seven connected car features were chosen by the project: electronic emergency brake light (EEBL); green light optimal speed advisory (GLOSA); emergency vehicle warning (EVW); intersection movement assist (IWC); intersection priority management (IPM); in-vehicle signage (IVS); and collaborative parking which were successfully demonstrated on public roads across the two host cities. This study had not opened the access of any technical report related to this project, which limited the parameter justification.

3. RTCPM FOR CRASH RISK EVALUSTION

(1) Simulation Environment

In this chapter, we introduce the real-time crash prediction model (RTCPM) instead of SSMs for evaluating the crash risk. First, a twenty four hours micro-simulation was conducted in VISSIM with traffic data for 8th April 2014 from the route 4 inbound direction, since no crash occurred on that day. Traffic data and traffic volume at 1 min interval were used as input variables. Simulation was conducted for the entire route which was divided into five segments at kilo-post locations 12.55, 9.72, 6.72, 5.49 and 2.93 km. The GEH statistic (named after Geoff E. Havers) was used (Eq. (1)) to evaluate the extent to which the simulated data matches the original data, which is widely accepted and used in the literature (Abdel-Aty et al., 2020).

$$\text{GEH} = \sqrt{\frac{2(M-C)^2}{M+C}} \tag{1}$$

where,

M : simulated traffic volume, and

C : actual traffic volume collected from detectors.

GEH values were calculated for flow and speed data (per minute) at five kilo-post locations. The average GEH value for volume/ min, and speed/ min for all five kilo-post locations were found to be below five. Hence, the route was well calibrated and validated. After calibration of base model, simulation was conducted under mixed scenarios where only passenger cars and automated vehicles (AVs) (car) were considered. Five scenarios were developed and run for analysis by a combination of different AV penetration rates which were: 0%, 20%, 40%, 60%, and 80%. The penetration rate of 0% represents the base scenario with current traffic environment with no AV. On the other hand, the penetration of 100% represents a fully AV environment. In this study 100% scenario was excluded because from the literature review it was clearly found that at 100% penetration conflicts are almost zero for AVs as AVs show highly cautious behavior and also full scale benefits can be found at that rate.

(2) Driving Behavior for Human Driven Vehicle and Automated Vehicle

In this study, t he built up driving behavior models of VISSIM for both human driven vehicle and AV were used since these models were already calibrated and validated using real-world data in the CoEXist project, 2020. Cautious, normal and all knowing driving logics were used. Car following parameters and lane changing parameters were represented in the Table 1 and Table 2. Furthermore, for human driven vehicle free-flow speed which was determined from the nearest upstream detector data was set as the desired speed. For AV, desired speed was fixed at 80 km/h for cautious and normal driving logics while 90 km/h was set for all-knowing driving logic by considering that even at higher speed, AVs are assumen to be capable of maintaining safe behavior such as safe distances between vehicles.

Table 1 Wiedemann 99 Car following parameters for different driving logics

Parameters	Unit	Description	Human Driving Vehicles	Normal driving logic	Cautious driving logic	All-knowing driving logic
CC0	m	The average standstill distance	1.5	1.50	1.50	1.0
CC1	s	The headway time	0.90	0.90	1.50	0.6
CC2	m	The distance difference in the oscillation condition	4	0	0	0
CC3	s	Controls the deceleration process	-8	-8	-10	-6
CC4 (-)	m/s	Defines negative speed difference	-0.35	-0.1	-0.1	-0.10
CC5 (+)	m/s	Defines positive speed difference	0.35	0.1	0.1	0.10
CC6	1/(m*s)	Influence of distance on speed oscillation while in following process.	11.44	0	0	0
CC7	m/s^2	Oscillation acceleration: actual acceleration during the oscillation process.	0.25	0.1	0.1	0.10
CC8	m/s^2	Standstill acceleration: desired acceleration when starting from standstill	3.5	3.5	3	4
CC9	m/s^2	Acceleration at 80 km/h: desired acceleration at 80 km/h	1.5	1.5	1.2	2

Table 2 Lane change behavior for different driving logics

Behavioral functionality	Human Driving Vehicles	Normal driving logic	Cautious driving logic	All-knowing driving logic
Advance merging	On	On	On[a]	On
Cooperative lane change	Off	On	On[a]	On
Safety distance reduction factor (m)	0.6	0.6	1+EABD[b]	0.75
Minimum headway (m)	0.5	0.5	1	0.5
Maximum deceleration for cooperative braking (m/s2)	-3	-3	-2.5	-6

[a] *If the vehicle cannot detect that other vehicle wants to change lanes, the value should be off/zero*

[b] *EABD (enforce absolute breaking distance) must be on*

(3) Dynamic Bayesian Network

Bayesian Network (BN) is a probabilistic graphical model that expresses the probability relationships among a set of variables that connect those variables in a directed acyclic graph (DAG). Dynamic Bayesian Network, a kind of BN, can couple time-series data to express the risk evolving process with time flowing forward (Liu et al., 2021). DBN also expresses probabilistic dependencies of random variables in time sequence under the probabilistic inference. Dynamic Bayesian Network (DBN) can express dependencies within one time slice as well as dependencies among time slices. A DBN consists of the probability distribution function (PDF) for the sequence of T hidden state variables X = $\{x_0,\ldots\ldots,x_{(T-1)}\}$ and the sequence of T observable variables Y = $\{y_0,\ldots\ldots\ldots,y_{(T-1)}\}$, where T is the time boundary for the given event under investigation. This can be expressed as:

$$Pr\,(X,\ Y) = \prod_{t=1}^{T-1} \Pr(x_t \,|\, x_{t-1}) \prod_{t=0}^{T-1} \Pr(y_t \,|\, x_t)\, \Pr(x_0) \tag{2}$$

To completely specify a DBN, three sets of parameters must be defined: state transition PDFs, $\Pr(X_T\,|X_{T-1})$ which specify time dependencies between the states; observation PDFs, $\Pr(Y_T\,|X_T)$ which specify dependencies of observation nodes regarding other nodes at time t; and initial state distribution $\Pr(X_0)$ which brings initial probability distribution in the beginning of the process.

(4) Fundamental Diagram

To understand the traffic situation under mixed scenario of AVs and human driven vehicles : maximum flow (veh/hr), free-flow speed (km/hr) and jam density (veh/km) were caluculated (Table 3), and the fundamental diagram (FD) was generated from VISSIM simulation data with the parameter setting for AV based on three driving behaviors: cautious, normal, and all-knowing.

Table 3 Parameter estimation from FD

Driving behavior	MPR,%	Maximum flow, q_{max} (veh/hr)	Free-flow speed, v_{ff} $(\frac{km}{hr})$	Jam density, k_j,(veh/k)
	Base, 0%	4920	156	100
Cautious	40%	4740	167	37
	80%	4620	173	89
Normal	40%	5220	165	95
	80%	5040	172	102
All-knowing	40%	5160	145	110
	80%	5100	183	110

Since the study route was divided into five segments, FD was developed only for one segment which is 2.2 km long. Table 3 indicated that under cautious driving with 40% AV and 80% AV penetration, jam density is lower not only than base scenario but also than two other scenarios (normal and all-knowing). The possible reason is that with cautious driving, vehicles maintain larger gap than human driven while normal is similar to human, and all-knowing generates the smallest gap. Figure 2 to Figure 4 showed the FD with 40% AV under all-knowing, normal, and cautious driving environment.

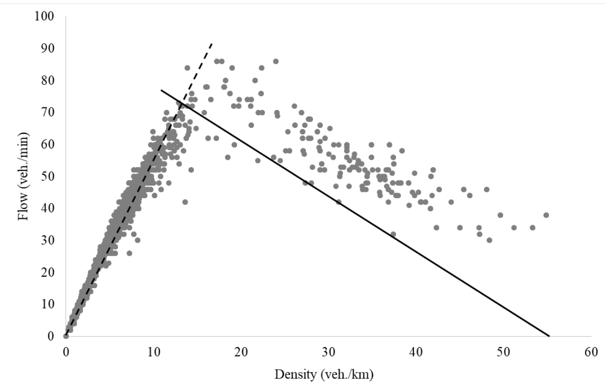

Fig. 2 FD for 40% AV under all-knowing driving environment

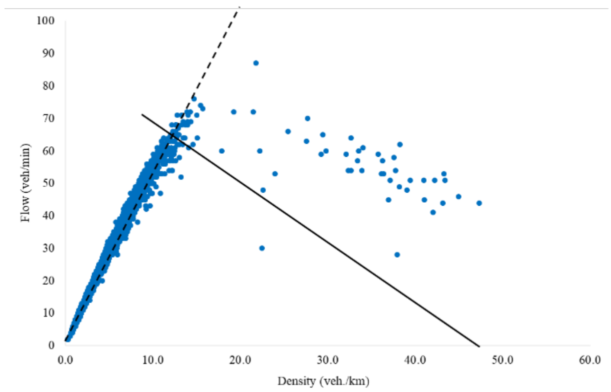

Fig. 3 FD for 40% AV under normal driving environment

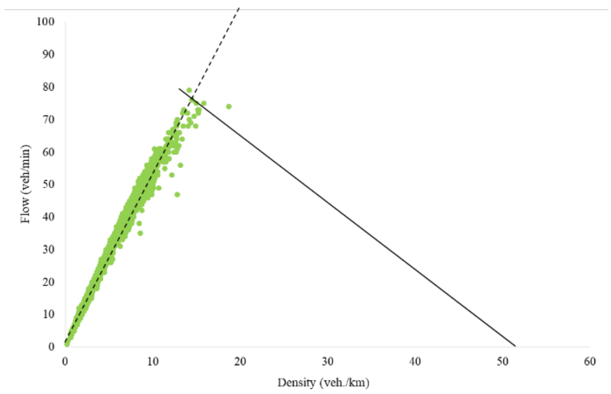

Fig. 4 FD for 40% AV under cautious driving environment

Table 4 Number of events with a risk of threshold > 5 for DBN under different driving logics

Driving logic		MPR, %				
		Base 0%	20%	40%	60%	80%
Normal	No. of events	1393	1335	1311	1272	1239
	% change	-	-4.2	-5.9	-8.7	-11.1
Cautious	No. of events	1393	1359	1310	1268	1210
	% change	-	-2.4	-6.0	-9.0	-13.1
All-knowing	No. of events	1393	1417	1338	1310	1245
	% change	-	+1.7	-3.9	-6.0	-10.6

+ = crash risk increase
- = crash risk reduction

(5) Automated Vehicle Implementation into Dynamic Bayesian Network (DBN)

DBN model was used to predict the crash risk. This study built only one three-time-sliced (each for one minute) model where selected variables were difference between upstream and downstream flow (q), difference between upstream and downstream speed (v), and downstream speed (d_speed). The model was constructed with 71 crash and 1244 normal data. On the other hand, 30 crash and 542 normal data were used for model validation. Based on overall accuracy and probability of crash likelihood model performance were calculated (Roy et al., 2022). From RTCPM performance evaluation it was found that at threshold value of 5 (five), the model detected 40.0% of the crashes and the overall accuracy which included the correctly predicted crash and normal cases was 74.1%. Hence, for this study, a threshold of 5 (five) was chosen for predicting the crash risk.

The crash risk was analyzed for all five scenarios for three driving behaviors. By using threshold values to “>5” for DBN, the crash risk was identified for each driving environment. Results (Table 4) exhibited that in every case using threshold >5 crash risk decreases for 80%AV implementation by 11.1%, 13.1, and 10.6% respectively.

Table 4 indicated that when AVs followed the normal driving behavior, the crash risk decreased with the increase of penetration rate under mixed case scenario. The results showed that with normal driving behavior where AVs almost behave like human-driven vehicles, the risk reduced from 0% to 80% AV scenario by 11.1%. In case of cautious driving behavior of AV, where drivers of AV always respect the road code and safe behavior, the risk decreased with the increase of AV from 0% to 80% by 13.1%. On the other hand, with all-knowing driving behavior, where drivers behave more aggressively with smallest gap, the risk reduced from 3.9% to 10.6% with the AV penetration rate 40% to 80%. Since the DBN model was developed for human driven vehicles, the results should be considered as the crash risk from the viewpoint of human driven vehicles, for example, 20% of the total vehicles under 80% of AV penetration rate.

With higher MPRs, some of the driving volatility measures were reduced such as less lane changing, which lead to maintaining homogeneous speed and headways. Also, because of more cautious behavior of AV, AVs always maintain safe gap (which is higher than human driven vehicle) (Dong et al., 2021), and safe time headway (Deluka Tibljaš et al., 2018; Zhang and Gao, 2020), which also contributes to a greater benefit on traffic safety by reduction in the number of dangerous situations. These findings are consistent with the previous studies (Ye and Yamamoto, 2019; Arvin et al., 2018; Rahman et al., 2018; Zhu and Tasic, 2021; Li et al., 2022; Rahman et al., 2019).

Furthermore, results showed that with 20% AV risk increases 1.7% under all-knowing driving environment. This is because human drivers are not be able to adapt to the robust and syn-chronised driving behaviour of AVs under this environment with low penetration rate of AV. AVs with 0.75 m headway may disrupt the order and uniformity of the flow since the human driven vehicles drive with a headway significantly higher than that. Sinha et al. (2020a) and Virdi et al. (2019) also found the similar results in their studies.

4. CONCLUSIONS AND FURTHER STUDIES

Since AV data are less available currently, the study on large scale deployment of automated vehicles in the real world is now a challenging issue. To tackle this issue, setting appropriate parameter while conducting simulation based analysis is very important. On the other hand, all preceding studies estimated crash risk based on surrogate safety measures which has some crucial drawbacks. So, finding alternative assessment models instated of surrogate safety measures are also needed to be considered. By considering these issues, this study focused on appropriate parameter setting for AVs, and later on the introduction of the real-time crash prediction (RTCP) model-based crash risk evaluation using Dynamic Bayesian Network (DBN). RTCPM based results showed that under mixed scenario with the increase of AV penetration, the crash risk decreased for different driving environments by 11.1%, 13.1%, and 10.6% respectively. Since the DBN model was developed for human driven vehicles, the results should be considered as the crash risk from the viewpoint of human driven vehicles.

Like other studies this study is not free from limitations. The dynamic Bayesian based model for this study was developed based on real-time human driven vehicles data. Since AV data currently are less available so it was assume that under mixed scenario DBN can estimate the crash risk in real-time. But when AV market share reaches 80%, then almost all vehicles are AVs. From reviewing previous studies, it is expected that with high market share they are almost crash free. In that case, DBN model may not be the suitable solution.-Furthermore, parameters for human driven vehicles and AVs were set based on previous studies which may require more clarification for further analysis.

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