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RESEARCH ARTICLE

# Improved Collision Risk Assessment for Autonomous Vehicles at On-Ramp Merging Areas

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**ABSTRACT** Unsafe lane-changing maneuvers contribute to accidents and merging conflicts due to variations in traffic states and driver behaviors at on-ramp merging areas. Connected and autonomous vehicle (CAV) technologies promise significant improvements to traffic management systems, including the possibility of reducing collisions. CAVs provide various driving supports, which are expected to reduce collisions by exploiting information from surrounding vehicles. This paper proposes a collision avoidance (CA) model that predicts the occurrence of collision events associated with different vehicle movements in merging areas. A decision-making system consisting of a threat assessment model is proposed to assess the risks associated with different movements, and to avoid collisions based on safe lateral and longitudinal acceleration of the on-ramp vehicle in the merging area. Then, evasive action of the main lane vehicle is assessed based on its braking response during the merging interaction with the on-ramp vehicle. Finally, in emergency situations, a vehicle stabilization mechanism is introduced to preserve the vehicle states within the envelope of danger. The results show that the model could be used to avoid collisions in multiple scenarios and predict the occurrence of collision events associated with different vehicle movements. Moreover, we demonstrate the effectiveness of the proposed model using the Next Generation Simulation (NGSIM) I-80 trajectory dataset. The findings show that the proposed model can be useful for avoiding collisions in real-time scenarios. In summary, the proposed CA model provides a valuable safety management tool.

**INDEX TERMS** Autonomous vehicles, collision avoidance, on-ramp merging, safety, threat assessment.

## I. INTRODUCTION

Advanced driver assistance systems (ADAS) play a key role in the automotive industry, due to a large number of accidents caused by driver negligence [1] and human error [2]. The most recent World Health Organization data reported that approximately 1.3 million people lost their lives in traffic and road accidents each year [3].

Connected and Autonomous Vehicles (CAVs) have the potential to reduce collisions, thereby, improving traffic and road safety [4]. Autonomous vehicles (AVs) are considered an essential component of intelligent transportation systems (ITS), which consists of various features, such as advanced decision-making systems [5], [6], recognition models, and control models [7]. These features can help drivers to make safe driving decisions. Recently, several works have examined the safety issues of CAVs under different traffic conditions, such as signalized intersections [8], [9], highway corridors [10], [11], roundabouts [8], and using different traffic networks [12].

Several machine learning techniques, such as support vector machines (SVMs), hidden Markov models (HMMs), and artificial neural networks (ANNs) have been proposed in recent years. These techniques depend on decision-making logic that enables the developed model for assessing collision risks in urban traffic environments [13], [14], [15].

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In [15], Xiong et al. introduced a chain of road traffic incident (CRTI) model based on SVM, which has the ability to predict collisions in complex traffic scenarios. Several methodologies can be used to improve the detection of collisions, such as independent component analysis (ICA) [16], vehicle-to-everything (V2X) technology [17], [18], [19], object identification-based method [20], and Gaussian mixture models [21]. Some authors have employed a decision-making based detection model to address uncertainty in traffic conditions and drivers' attitudes about driving [22], [23].

Decision-making algorithms play a crucial role for avoiding collision risks, as discussed in [24]. Various collision avoidance (CA) applications have been benefitted from advanced technologies such as, decision-making [6], trajectory planning [25], and motion control techniques [26]. They are successfully applied in CAVs or advanced driver assistance system (ADAS) to mitigate the collision risks [27], [28] and to improve driver's safety. To date, the CA methods can be divided into different categories such as learning-based models [29], [30], motion planning-based models [31], [32], [33] and collision risk assessment models [34], [35], [36].

To date, just a few decision-making models aimed at mitigating the collision risks of CAVs have been proposed [37], [38], [39]. Those methods considered different problems than the problem solved in this research. First, they considered the simple vehicle trajectory path in the main lane and determined the collision risk in a simplified motorway environment by considering three main lane vehicles without modeling the merging maneuver. Also, these methods did not investigate the collision risks associated with the on-ramp vehicle movements. Finally, these approaches did not employ the vehicle stabilization model to prevent the colliding vehicle further to avoid collision with surrounding vehicles or other objects on the road.

The CA models play a crucial role in ensuring the safety of connected and automated vehicles. Recently, several studies have been presented, which aim to investigate rear-end collision risks in terms of an automated braking system [40], a rear-end collision warning method based on a stochastic local multivehicle optimal speed model [41], and autonomous steering [42]. The main issue associated with rear-end collision avoidance techniques is that they depend on the strategy to achieve the desired deceleration. For instance, most automakers have embedded cars with autonomous emergency braking systems. These are expected to warn drivers to apply the brakes in emergency conditions [42], [43], [44]. Moon et al. [45] evaluated an adaptive cruise system with the CA framework. They proposed three different control strategies based on different driving situations, such as safe, warning, and dangerous modes. They tuned the control parameters with the commonly used confusion matrix method by considering manual driving data. The proposed model was tested on the real vehicle by considering safe and unsafe traffic conditions. Although, the risks of rear-end collision can be overcome using the emergency braking mechanism (EBM). However, there are several limitations, such as when the subject vehicle travels at a higher speed or when the distance between the subject vehicle and the lead vehicle is smaller [46].

The advanced technologies embedded in CAVs can deal with emergency traffic conditions, such as emergency lane changing maneuvers, which occur when vehicles encounter a dangerous situation while changing lane, and emergency collision avoidance, in which the event occurs in a short time and requires immediate input along with a higher yaw (angular velocity) rate. Under these conditions, the vehicle tires are unstable and begin to slip, which destabilizes the vehicle after the collision is avoided. He et al. [47] proposed an emergency steering control strategy to avoid a potential collision. The proposed model has a decision-making layer, which evaluates collision risks and determines vehicle destabilization. Then, they controlled the vehicle's lateral motion by considering an external disturbance and tire cornering response. Similarly, Cui et al. [42] proposed a new strategy for avoiding rear-end collision in the highway traffic environment. They divided the CA process into two different stages, such as guiding a vehicle to travel on the adjacent lane and the centerline of the lane. Also, they designed the braking and vehicle stabilization system as a requirement of the proposed CA method. Cui et al. [48] proposed a model for emergency avoiding collisions by considering nearby traffic. They developed the CA model considering two different modules such as the estimator and predictor modules. Then, they developed a model considering nearby traffic in the overlapping zone. Recently, Sheikh and Peng [27] proposed a collision risk assessment model for on-ramp merging vehicles based on the probabilistic approach. They demonstrated the effectiveness of the proposed CA model based on a path planning model and the findings show that the proposed model could improve the traffic safety by reducing the collision risk at on-ramp merging areas.

Similarly, threat assessment (TA) models are another approach to mitigating collision risks. These play a crucial role in assessing the risks posed by nearby vehicles and taking measures to avoid collisions [49]. Threat assessment methods can be further categorized into deterministic and probabilistic approaches [34]. Several methods have been presented to assess the risk level associated with the surrounding vehicles. Brannstorm et al. [50] presented a threat assessment model to avoid the collision. They employed the linear bicycle model commonly used to examine vehicle dynamics to determine the vehicle movements. The vehicle is represented in a rectangular region and an evasive maneuver is modeled to estimate different set of maneuvers, which the driver can use to avoid collisions. They tested the proposed threat model using real traffic scenarios. Similarly, Li et al. [34] proposed a model to assess collision risks based on a decision-making algorithm in different traffic scenarios. They designed the probabilistic model based assessment model using the conditional random field to determine the risk with surrounding vehicles. They tested the performance of the proposed model on the open source CARLA simulation platform in different traffic scenarios.

Zhou et al. [49] proposed a threat assessment model for intelligent vehicles (IVs) based on the drivers' evasive responses. The proposed model integrated the crash probability and crash state, which were used to avoid collision in various traffic scenarios. They extracted a total of 82 critical events from the Strategic Highway Research Program data to evaluate the performance of the model in different scenarios. The experimental results show that the 80 critical events were successfully identified as crashes. However, various crash events were misclassified due to limited observations. Katrakazas et al. [51] introduced an integrated collision risk assessment approach for CAVs. They integrated the network level with a vehicle level collision prediction to improve the effectiveness of assessing the risk of CAVs in real-time. The results show that the interaction aware model performance was increased up to 10% in traffic conflict conditions, but the proposed system did not completely identify traffic conflicts due to unpredictable driving behavior.

Although existing works have been used to avoid collisions with nearby vehicles, they have only focused on the safety analysis in merging areas. The first issue associated with the above-mentioned methods is that most of the work did not consider different vehicle movements at the on-ramp merging area and the vehicle destabilization caused by its movements, which can pose a threat to the surrounding vehicles. Second, most of the work focused on cooperative merging algorithms based on advanced communication technology, but they did not incorporate the driver decision-making algorithm, which could be helpful to assess the risks of collision at on-ramp merging area.

The main motivation of this paper is to develop a CA model at an on-ramp merging area. It employs a decision-making method consisting of a threat assessment model that continuously evaluates the collision risks of different vehicle movements at on-ramp merging area.

To summarize, the main objectives of this study are the following:

- We propose a decision-making model, consisting of a threat assessment model to assess the collision risk associated with different on-ramp vehicle movements, and to avoid collisions based on the safe lateral and longitudinal acceleration of the on-ramp vehicle (ORV) in the merging areas. In particular, we evaluate the risks with two different scenarios; when the ORV attempts to merge on the main lane and when the ORV intersects with the main lane vehicle and merges on the main lane.
- We evaluate the main line vehicle's (MLV) evasive response to the ORV's aggressive merging behavior when it attempts to merge into the main lane traffic. Under these conditions, the MLV applies emergency braking to avoid a collision in the on-ramp merging area. As a result, the MLV may collide with other vehicles or objects on the road when emergency braking is applied. Therefore, we introduce a stabilization model to stabilize the MLV envelope and limit vehicle states within that envelope.
- The results show that the proposed CA model can be used to avoid collisions by accurately predicting the collision events in different vehicle movements and therefore has the ability to improve traffic and road safety. Moreover, we have evaluated the performance of the proposed model using the NGSIM I-80 trajectory dataset. The findings show that the proposed model can be useful for avoiding collisions in real-time scenarios.

This paper is organized as follows. The methodology is discussed in Section II. Section III presents the proposed threat assessment and collision avoidance model. Section IV discusses the MLV evasive response and vehicle stabilization model. The simulation results are discussed in Section V, and finally conclusions and the future work are discussed in Section VI.

## II. METHODOLOGY

The complex interaction between the main lane traffic and the on-ramp traffic is extremely challenging due to unpredictable movements of on-ramp vehicles in merging areas, often increasing the collision risks between them and could cause road bottlenecks in the merging areas. Therefore, it is necessary to develop a CA model to determine the risks at on-ramp merging areas by considering different movements of on-ramp vehicles, and predicting the occurrence of collision events associated with them.

The proposed model aims to accomplish the above-mentioned tasks based on the decision-making model and vehicle evasive response and stabilization model, as illustrated in Fig. 1. We develop the decision-making model that aims to assess the collision risks associated with different vehicle movements and to avoid potential collision in on-ramp merging areas. In this study, decision-making is accomplished in two steps: (1) a collision threat assessment model that continuously evaluates the collision risks associated with the on-ramp vehicle in multiple scenarios (2) the CA model is used to avoid collisions based on the safe lateral and longitudinal acceleration of the ORV in merging areas. Then, we determine the evasive response of the MLV when the ORV attempts to merge into the main lane aggressively, and introduce a stabilization model in order to avoid the MLV colliding with other vehicles or objects while applying the emergency braking.

In the proposed system, we assume that both the main lane vehicle and on-ramp vehicle are traveling in the forward direction while the other vehicle (OV) is traveling in the adjacent lane as shown in Fig. 3. We assume that the collision is likely to occur at an on-ramp merging area (conflicting area) when the on-ramp vehicle tries to merge with the other vehicles on the main lane. The collision location is close to the conflicting merging area within the radius of the mainline vehicle. Note that we did not consider the OV in the collision avoidance scenario because it does not pose a threat. First,

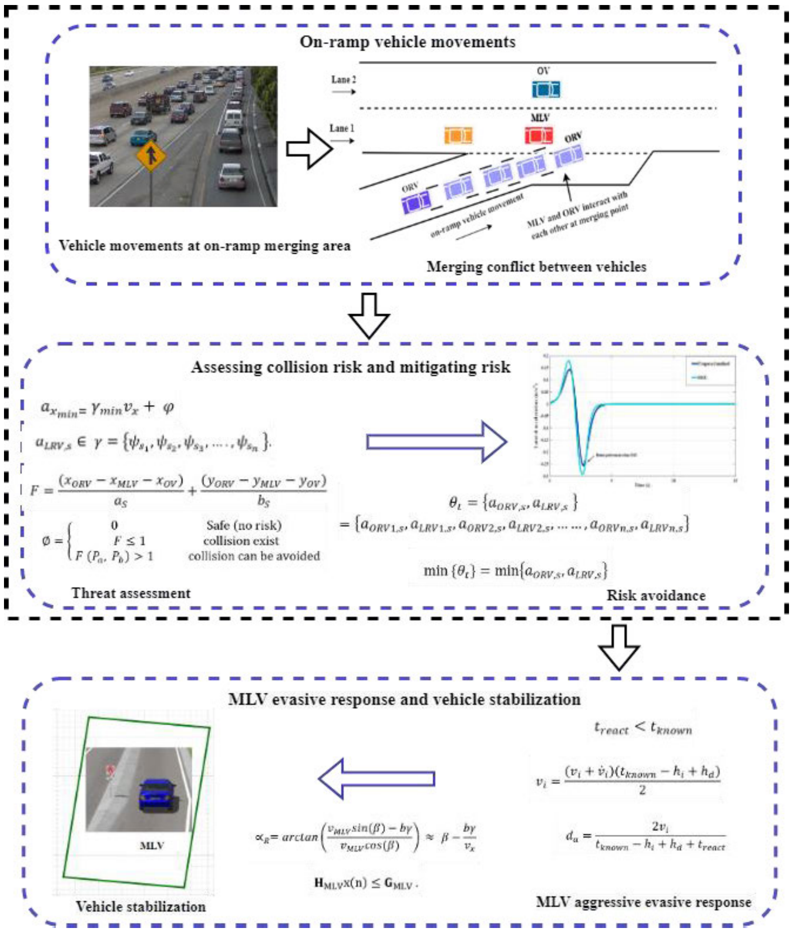



**FIGURE 1. Proposed collision avoidance model.**

we employed the threat assessment model to analyze and evaluate the collision risks in merging areas, such as when the ORV attempts to merge on the main lane and when the ORV intersects with the main lane vehicle and merges into the main lane. Then, we determine the main lane driver's evasive action in response to the on-ramp vehicle. It was determined based on the MLV braking response (braking pedal force) when the ORV attempts to merge on the main lane. The main lane driver decelerates to maintain the sufficient distance, which will reduce its collision risks. Then, we introduced a vehicle stabilization process to stabilize the main lane vehicle in case of emergency collision avoidance. The stable envelope is designed to limit the vehicle states and could be useful to analyze the steady-state capabilities of tires.

## III. RISK ASSESSMENT AND COLLISION AVOIDANCE MODEL

### A. RISK ASSESSMENT MODEL

This section discusses the threat assessment model for avoiding collision between the MLV and ORV when the ORV attempts to merge with the MLV on the main lane. In the collision avoidance scenario, we consider a single lane-changing maneuver is performed, in order to avoid the collision when the ORV merges on the main lane and interacts with the MLV and other vehicle (OV). A fifth-order polynomial equation can be used to define the vehicle lane changing path, as discussed in [47], and written as follow:

$$y = b^T x + c, \tag{1}$$

The Eq. (1) can be written as below.

$$b = [b_0\ b_1\ b_2\ b_3\ b_4\ b_5]^T\ ,$$
$$x = \left[1\ x\ x^2\ x^3\ x^4\ x^5\right]^T\ ,\ \text{and } c = [1\ 1\ 1\ 1\ 1\ 1]$$

where $x$ and $y$ denote the longitudinal and lateral positions of the ORV, respectively, $b$ is the coefficient with $n$ ranges [$n$= 0, 1, ., 3], and $c$ denotes the constant path of the other vehicles (MLV and OV). Note that, the other vehicles are traveling on the same path and do not perform lane changing maneuvers. Therefore, we selected the constant path for other vehicles in (1). The polynomial equation can be used to identify the lane-changing path of the on-ramp vehicle and to avoid collisions between the ORV and other vehicles.

We set the initial boundary conditions of the fifth-order polynomial as $y\left(x_o\right) = 0,\ \acute{y}\left(x_0\right) = 0,\ \dot{y}\left(x_0\right) = 0 y\left(x_T\right) = y_T,$

**TABLE 1.** Collision risks analysis of vehicle movements at different times.

| Prediction time (s) | Scenario 1 ($t = 0\ s$) | | Scenario 2 ($t = 0.2\ s$) | | Scenario 3 ($t = 0.50\ s$) | | Scenario 4 ($t = 0.75\ s$) | |
|---|---|---|---|---|---|---|---|---|
| | ORV left region | ORV right region | ORV left region | ORV right region | ORV left region | ORV right region | ORV left region | ORV right region |
| 0 | 18.11 | 18.58 | 18.11 | 18.58 | 18.11 | 18.58 | 18.11 | 18.58 |
| 5 | 11.21 | 16.01 | 9.60 | 16.01 | 8.11 | 16.01 | 7.77 | 16.01 |
| 10 | 7.60 | 13.82 | 4.89 | 13.82 | 4.02 | 13.82 | 3.12 | 13.82 |
| 15 | 5.80 | 11.58 | 3.72 | 11.58 | 0.99 | 11.58 | 0.88 | 11.58 |

$\acute{y}(x_T) = 0$, $\dot{y}(x_T) = 0$. The ORV cut in path in terms of boundary conditions can be written as below:

$$n = \frac{dy/dx}{\left[1 + \left(\frac{dy}{dx}\right)^2\right] + 1}, \tag{2}$$

where $x_o$ and $y_o$ are the initial longitudinal and lateral positions of the ORV at the beginning of collision avoidance when the ORV attempts to intersect on the main lane, respectively. $x_0$= 0, $x_T$, and $y_T$ are the longitudinal and lateral terminal positions when the ORV avoids collision with the main lane vehicle, respectively. $n$ denotes the ORV cut-in path when it attempts to merge on the main lane.

We can substitute Equation (1) into above boundary conditions at which the ORV merges with MLV, the relationship can be formed as below.

$$ba = [0\ 0\ 0\ y_T\ 0\ 0]^T. \tag{3}$$

Similarly, after solving the Equation (3), we can obtained b, as below.

$$b = [0\ 0\ y_T\ y_T x^3\ -y_T x^4\ y_T x^5\ ]^T. \tag{4}$$

The collision-free path of the ORV can be obtained after combing the Equation (1) and Equation (4), as written below.

$$y(x) = y_T x + c + y_T x^4 + c - y_T x^5 + c + y_T x^6 + c. \tag{5}$$

After simplifying Equation (5) can be written as below.

$$y(x) = y_T x + y_T x^4 - y_T x^5 + y_T x^6 + 4c. \tag{6}$$

Equation (6) represents the collision-free path when the on-ramp vehicle merges into the main lane traffic and ensures that there is no risk of collision during the merging process. The collision-free path only considers the vehicle kinematics conditions. In this study, we consider the threat assessment model and the risks of vehicle destabilization to determine the collision risks in emergency conditions.

The lateral acceleration of the ORV when entering the on-ramp merging area can be written as below.

$$a_i = v_x \gamma + v_y + G. \tag{7}$$

where $\gamma$ denotes the yaw rate, $v_x$ and $v_y$ denote the longitudinal and lateral velocity, respectively. $G$ is the gravitational acceleration, which has the value of $9.8m/s^2(32.152\,ft/sec^2)$ [47].

The minimum constant yaw rate could satisfy the demand of avoiding collision between the ORV and the MLV, as discussed in [48] (see Fig. 3), which can be written as below:

$$\gamma_{min} = \frac{v_x P_b}{P_a^2 + P_b^2 + x_n^2 - \frac{w_C}{2}}. \tag{8}$$

where $v_x$ denotes the velocity of the ORV, $P_a$ and $P_b$ is the longitudinal and lateral distance between the ORV and the MLV, $w_c$ is the width of the ORV, which is set about less than 2.6 m.

Next, after combining the minimum yaw rate in Eq. (8) with the vehicle velocity and the relative yaw angle, the minimum available lateral acceleration $a_{x_{min}}$ can be modeled as below. Note that, the minimum available lateral acceleration could be used to avoid the collision.

$$a_{x_{min}} = \gamma_{min} v_x + \varphi, \tag{9}$$

Also,

$$a_{x_{min}} = \frac{v_x^2 P_b}{P_a^2 + P_b^2 + x_n^2 - \frac{w_c}{2}} + \varphi. \tag{10}$$

where $\varphi$ denotes the relative yaw angle of the ORV.

The vehicle collision risk model in terms of ORV lateral acceleration. It consists of various safe sets, which indicates that the distance between the ORV and the MLV is enough to avoid collisions. The available lateral acceleration of the ORV can define as the safe set $\theta_{s_i}$ and can be written as follows.

$$a_{ORV,s} \in \gamma = \left\{\theta_{s_i}\right\}, \tag{11}$$

$$a_{ORV,s} \in \gamma = \left\{\theta_{s_1}, \theta_{s_2}, \theta_{s_1}, \ldots, \theta_{s_n}\right\}. \tag{12}$$

Similarly, the safest longitudinal set can be written as follow.

$$a_{LRV,s} \in \gamma = \left\{\psi_{s_1}, \psi_{s_2}, \psi_{s_3}, \ldots, \psi_{s_n}\right\}. \tag{13}$$

We have defined the collision avoidance function to evaluate the collision risk between the ORV and the MLV, and considered that the MLV vehicle is within the elliptical region. The ellipse parameters are correlated with the MLV, which can be determined based on the axes parameters. Therefore, we assumed that $a_s$ and $b_s$ are the safe major and

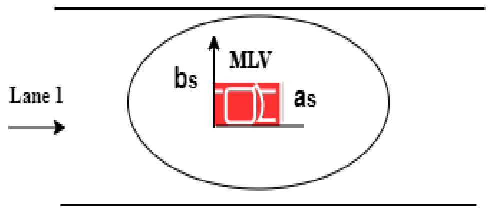
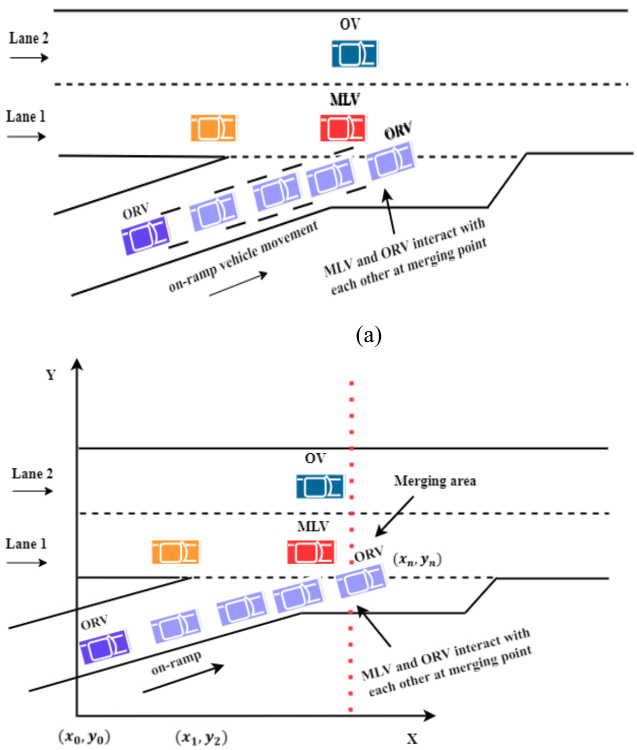



**FIGURE 2.** Elliptical position of the MLV.




(b)

**FIGURE 3.** Vehicle traveling at conflicting area, (a) MLV and ORV movements without risks, and (b) MLV and ORV interact at merging point.

minor axes of the ellipse, respectively, as shown in Fig. 2. The length of the MLV $L_{ML}$ in the elliptical region is set about 4 m.

Considering the ORV with surrounding vehicle positions (MLV and OV) on the estimated region (see Fig.3), the collision risk function with nearby vehicles in the elliptical region can be formulated as below.

$$F = \frac{(x_{ORV} - x_{MLV} - x_{OV})}{a_S} + \frac{(y_{ORV} - y_{MLV} - y_{OV})}{b_S}. \tag{14}$$

where $x_{ORV}$ and $y_{ORV}$ denotes the $x$ and $y$ positions of the ORV for the future event at any time $t$.$x_{MLV}$ and $y_{MLV}$ denotes the position of the MLV. Similarly, $x_{OV}$ and $y_{OV}$ denotes the positions of the OV. Note that, we apply the coordinates system to determine the accurate positions of the vehicles.

In the collision avoidance scenario, we first determine the positions of the MLV and ORV vehicles within the safe set of lateral and longitudinal accelerations $\{\theta_{s_i}, \psi_{s_i}$.

$$\emptyset = \begin{cases} 0 & \text{Safe (no risk)} \\ F \leq 1 & \text{collision exist} \\ F\,(P_a, P_b) > 1 & \text{collision can be avoided} \end{cases} \tag{15}$$

where Ø represents the threat assessment parameter.

### B. COLLISION AVOIDANCE MODEL

Collisions can be avoided based on the safe lateral and longitudinal acceleration of the ORV in merging area. The safe accelerations are put into the collision avoidance set $\theta_t$ as follows.

$$\begin{aligned} \theta_t &= \left\{a_{ORV,s}, a_{LRV,s}\right\} \\ &= \left\{a_{ORV1,s}, a_{LRV1,s}, a_{ORV2,s}, a_{LRV2,s}, \ldots\ldots, \right. \\ &\qquad \left. a_{ORVn,s}, a_{LRVn,s}\right\}. \end{aligned} \tag{16}$$

When the set $\theta_t$ is empty, then there are risks of collision between vehicles, since the gap between vehicles is smaller. Therefore, it is necessary to apply the emergency brake in order to avoid collisions. Note that, the emergency braking could destabilize the vehicle movement. As a result, the vehicle may collide with other vehicles or objects on the road. To overcome this issue, we determine the evasive response of the main lane vehicle and introduce a method for stabilizing the vehicle, as discussed in Section IV. If the set $\theta_t$ is not empty, then there is no collision risk in merging area, and thus no emergency braking is required, but the minimum safe lateral acceleration could be used to handle the steering maneuver, as follows:

$$\min\{\theta_t = \min\left\{a_{ORV,s}, a_{LRV,s}\right\}. \tag{17}$$

## IV. DETERMINE EVASIVE RESPONSE AND VEHICLE STABILIZATION

### A. MLV EVASIVE RESPONSE

This section evaluates the MLV interaction and the response to the ORV behavior when the ORV attempts to merge on the main lane. In particular, the MLV applies the brakes to maintain the safest distance or has enough gap between both vehicles when the ORV attempts to merge on the main lane, resulting in a smaller headway between them.

In the MLV evasive action response, we consider that the MLV only knows the intention of the ORV at a specific time $t_{known}$ before the ORV merges into the merging area (see Fig. 4). Hence, the MLV will arrive in the merging area at $t_{known}$ without applying brakes. As the initial headway between both vehicles is $h_i$, the expected arrival time of the ORV is $t_{known} - h_i$.

If the MLV takes a longer reaction time $t_{react}$ to the ORV merging behavior and maintain the headway $h_d$ from the ORV, then the expected arrival time of the ORV at merging area is $t_{known} - h_i + h_d$ We consider that the $t_{known}$ is the known time of the MLV at which the MLV realizes the merging interaction of the ORV when the ORV approaches at the

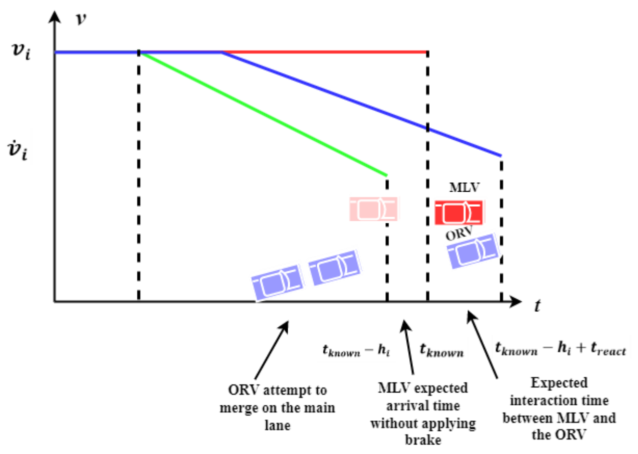



**FIGURE 4.** **MLV response to the ORV.**

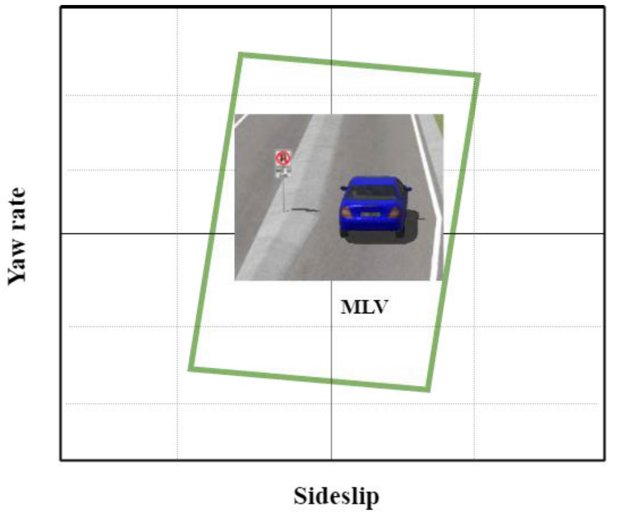



**FIGURE 5.** **The MLV stabilization envelope.**

merging area.

$$t_{react} < t_{known} \tag{18}$$

The MLV reacts with the ORV response by applying the brakes with a higher deceleration rate ($d_{max}$) and to maintain a larger headway between them. As a result, it could significantly reduce the collision risks when the ORV aggressively attempts to merge on the main lane.

$$v_i = \frac{(v_i + \dot{v}_i)(t_{known} - h_i + h_d)}{2}. \tag{19}$$

where $v_i$ denotes starting speed of the MLV, $\dot{v}_i$ is the speed of the MLV after applying brakes when approaching the merging area, $h_i$ is the initial headway of the MLV, and $h_d$ denotes the desired headway of the MLV.

Similarly, the slower speed of the MLV can be written as.

$$\dot{v}_i = v_i - d_a\left(t_{known} - h_i + h_d + t_{react}\right). \tag{20}$$

The deceleration rate can be represented as below.

$$d_a = \frac{2v_i}{t_{known} - h_i + h_d + t_{react}}. \tag{21}$$

where $d_a$ denotes the deceleration rate, in which the MLV performs the evasive response by applying the brakes, in order to maintain the desired headway between the MLV and the ORV.

### B. VEHICLE STABILIZATION

This section discusses the vehicle stabilization process of the MLV. After collision avoidance, the vehicle needs stabilization. Therefore, we use the stable envelope that limits vehicle states within the designed envelope as shown in Fig. 5. These limits could be useful for producing the steady-state of tires, as discussed by Beal and Gerdes [52]. Therefore, the stabilization of the vehicle states within the designed envelope. The steady state analysis of the yaw rate and sideslip should not be more than the steady-state values of the MLV tire, which can be yield as below.

$$r_m = \frac{F_{yf}}{m_{MLV} U_m}. \tag{22}$$

where $r_m$ denotes the steady state of yaw rate, $F_{yf}$ and $m_{MLV}$ are the lateral force of the MLV tire and the mass of the MLV, respectively. $U_m$ is the measurement parameter of the MLV.

The saturation of rear tires of the main lane vehicle is considered the limitation of the vehicle stabilization, as highlighted by Brown et al. [53]. The rear slip angle $\propto_R$ generates the maximum lateral forces for the main lane vehicle tire and can be written as follows:

$$\propto_R = arctan\left(\frac{v_{MLV} sin(\beta) - b\gamma}{v_{MLV} cos(\beta)}\right) \approx \beta - \frac{b\gamma}{v_x}. \tag{23}$$

where $\beta$ denotes the sideslip velocity is states, $v_{MLV}$ is the velocity of the main lane vehicle, and $b$ represents the distance between mass center to the rear axles.

Next, we restrict the MLV states into the safe region, indicating that the MLV does not enter a state which could destabilize the vehicle. The restriction can be represented by a linear quality, as discussed by Brown et al. [53], and is shown below.

$$\mathbf{H}_{\mathrm{MLV}}\,\mathrm{x}\,(\mathrm{n}) \leq \mathbf{G}_{\mathrm{MLV}}. \tag{24}$$

where $\mathrm{n} = 1, 2, \ldots, 10$

The vehicle state of the MLV can be stable if it moves outside of the envelope since its states are within the limits of the design envelope for a long time. The envelope could be useful for vehicle path planning such as, when the vehicle merges into different lanes and when the vehicle is out of the collision event.

## V. SIMULATION RESULTS AND DISCUSSION

Several simulation tests were conducted in different traffic scenarios to demonstrate the effectiveness of the proposed CA model.

**Algorithm 1** Pseudo-code for avoiding collision risk.

**Input:** $\emptyset$, $F$, MLV, $h_i$, $x_{ORV}$, $x_{MLV}$, $t_{known}$, $h_d$, $r_m$
**function** collision avoidance strategy ($\theta_t$), MLV evasive ($d_a$), stabilization $\mathbf{H}_{\mathrm{MLV}}$
$\emptyset$ = asses collision risk ($x_{ORV}, x_{MLV}$)
**if** $\emptyset = 0$ **then**
safe merging
**if** $\emptyset = F \leq 1$ **then**
low collision risks
**else**
higher collision risks at on-ramp merging area
**end if**
**if** $\theta_t = \left\{a_{ORV,s}, a_{LRV,s}\right\} = \{a_{ORVn,s}, a_{LRVn,s}$ **then**
collision risks can be avoided by minimum safe lateral acceleration
**else**
determine the collision risk
**end if**
**if** $h_i < h_d$ **then**
MLV arrives at merging area without applying emergency braking at $t_{known}$
**if** $t_{react} < t_{known}$ **then**
calculate $d_a$
**if** $d_a < d_{max}$ **then**
MLV react by applying the brakes with the normal deceleration rate to avoid collision risks and maintain the headway
**else**
vehicle destabilization caused by emergency braking
**end if**
**if** $r_m = \frac{F_{yf}}{m_{MLV} U_m}$ **then**
stabilize the steady states of MLV tire
**else**
MLV is not stabilize
**end if**
**if** $\mathbf{H}_{\mathrm{MLV}} x(n) \leq \mathbf{G}_{\mathrm{MLV}}$ **then**
MLV is stabilized within the envelop
**else**
MLV collides with other vehicle or objects on the road
**end if**
**end if**
**end function**

We generated two different traffic scenarios using the CarSim simulator, in order to validate the effectiveness of the proposed CA model. During the experiment, we sampled the position of the MLV and the ORV from 10 m and 20 m from the on-ramp merging point in the third scenario at $t = 0.50s$. While in the fourth scenario $t = 0.75s$, the distance between both vehicles is set to be 1 m to 2 m apart from each other to the on-ramp merging point (conflicting area). In the simulation, the numbers of vehicles of 546 and 892 were simulated in scenario 3 and scenario 4, respectively. The length of the MLV, ORV, and OV is set to be 1.8 m. The width of lane 1 is set to be 3.5 m with an on-ramp width of 3.2 m. The vehicles possess the radar sensors. They are placed on the front, and the sides of the vehicle.

In this study, we consider the two different scenarios, such as MLV and ORV vehicle movements without collision risks, and the interaction between them at merging point, as shown in Fig. 3. We used the CarSim traffic simulator to examine the proposed collision avoidance model. The traffic scenarios provide input to the Simulink model to determine the collision risks in the merging area.

### A. PERFORMANCE IN TERMS OF EMERGENCY CA MANEUVER

In this section, we evaluate the effectiveness of the proposed CA model using the emergency collision avoidance maneuver. We assume that the main lane vehicle could become unstable while avoiding a collision with the on-ramp vehicle when the ORV unsafely merges on the main lane. In the simulation, we consider the dry road surface ($\mu = 1$) and the vehicle velocity of $15m/s$, in order to demonstrate the effectiveness of the proposed CA model.

Fig. 6 shows the performance of the proposed model using the emergency collision avoidance maneuver on the dry road. We can see from Fig. 6(a) that the proposed model agrees well with the collision-free vehicle trajectory, indicating that there is no risk of collision between the MLV and ORV when the vehicles follow the reference path. The lateral acceleration comparison between the sliding mode control strategy (SMC) and the proposed method is shown in Fig. 6(b). We can see from Fig. 6(b) that the proposed method obtained a better collision avoidance in an emergency scenario as compared to the SMC. Fig. 6(c) shows that the proposed CA model obtains the lower and stable yaw rate as compared with the SMC method, meeting the demand to prevent the collision between the main lane vehicle and or-ramp vehicle. As shown in Fig. 6(e), the steering angle of the proposed method is stable and less oscillated than the SMC method, revealing that the proposed model meets the demand of avoiding collision between the MLV and ORV in the on-ramp merging area. We can see from Fig. 6(f) that the steering angle rate of the proposed model has a fast convergence rate than the SMC model, indicating that the proposed method could obtain a better collision avoidance in emergency situations.

### B. PERFORMANCE OF THE PROPOSED MODEL IN TERMS OF DIFFERENT TIME SPAN

This section evaluates the performance of the proposed collision avoidance model when the on-ramp vehicle merges on the main lane at different time spans. In the simulation, we consider the velocity of the MLV and ORV are $15m/s$ and $18m/s$, respectively and the initial acceleration of both vehicles is considered as $0m/s^2$.

Fig. 7 illustrates the vehicle movements of the MLV and the ORV at different time instances, such as $t = 0s$ (Scenario 1), $t = 0.2s$ (Scenario 2), $t = 0.5s$ (Scenario 3), and $t = 0.75s$ (Scenario 4). As shown in Fig. 7(a) and (b), both vehicles travel in different lanes. Therefore, there is no risk

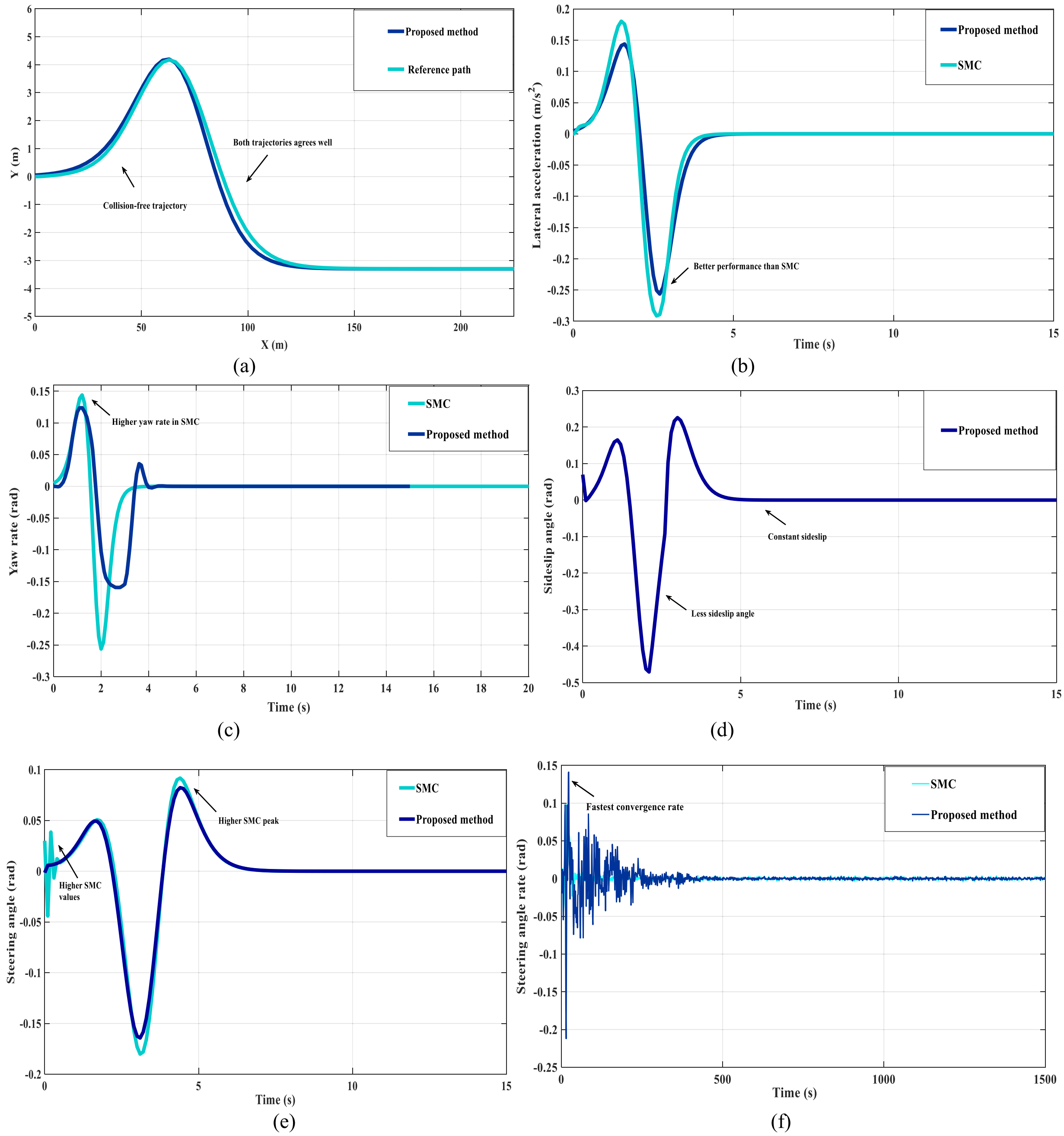



**FIGURE 6. The emergency collision avoidance maneuver on dry road, (a) vehicle trajectory, (b) vehicle lateral acceleration, (c) yaw rate, (d) sideslip angle, (e) steering angle, and (f) vehicle steering angle rate.**

of collision between the on-ramp vehicle and the main lane vehicle in scenario 1 and scenario 2 (see Fig. 7(a) and (b)). However, when the ORV merges on the main lane, as shown in Fig. 7(c) and (d). Therefore, there is a higher risk of collisions between the ORV and the MLV, especially when the ORV intersects the MLV in the merging area (scenario 4).

Fig. 8 shows the performance of the collision avoidance model at different simulation times. It aims to identify the collision risks associated with the ORV merging maneuver at different times. At time $t = 0s$, the main lane vehicle and the on-ramp vehicle travel on different lanes. Therefore, there is no risk of collision between them at the time. Analogues to $t = 0s$, there is no collision risk at time $t = 0.2s$. Since the ORV attempt to merge on the main lane and did not interact with the main lane vehicle. The MLV travels at a constant speed and can decelerate if the ORV approaches the main lane.

We can see from Fig. 8(c), there is a moderate collision risk when the on-ramp vehicle attempts to merge and interact with the main lane vehicle at time $t = 0.5s$. Similarly, the collision risk between the ORV and the MLV significantly increases when the ORV intersect with the MLV at time $t = 0.75s$ on

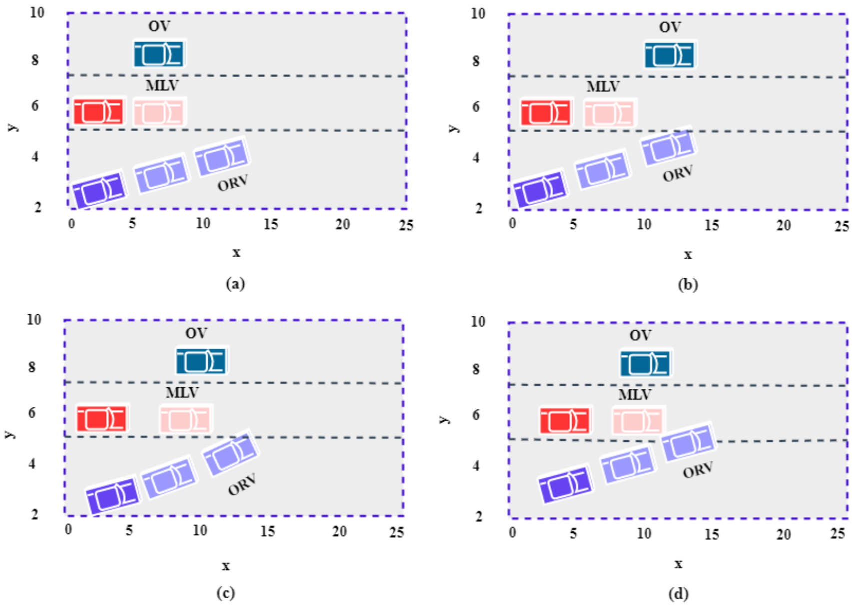



**FIGURE 7.** Vehicle movements with different time domain, (a) $t = 0s$, (b) $t = 0.2s$, (c) $t = 0.5s$, and (d) $t = 0.75s$.

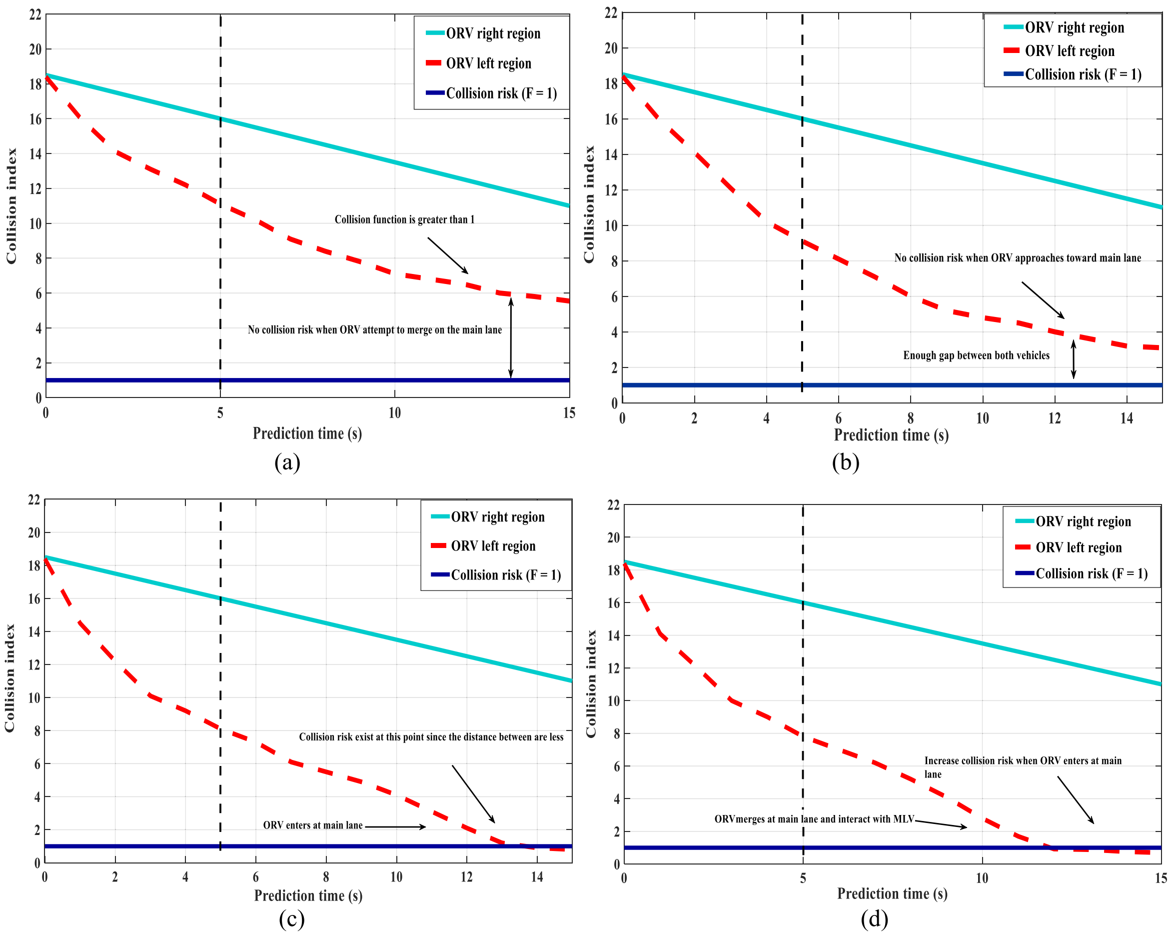



**FIGURE 8.** Collision avoidance with different simulation time domain, (a) $t = 0$ s, (b) $t = 0.2$ s, (c) $t = 0.5$ s, and (d) $t = 0.75$ s.

the main lane (see Fig. 8(d)). Under these conditions, the collision risk index $F$ is less than 1, which clearly indicates the collision risks between the MLV and ORV at the on-ramp merging area.

**TABLE 2. PDRF analysis of on-ramp vehicle movements with scenario 3 and scenario 4.**

| Scenarios | ORV attempts to merge (scenario 3 $t = 0.5\ s$) | | | | | | ORV intersects (scenario 4 $t = 0.75\ s$) | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Crash probability | | | Crash severity | | | Crash probability | | | Crash severity | | |
| | $t = 0$ | $t = 4$ | $t = 8$ | $t = 0$ | $t = 4$ | $t = 8$ | $t = 0$ | $t = 4$ | $t = 8$ | $t = 0$ | $t = 4$ | $t = 8$ |
| Case 1 | 0.00 | 0.19 | **0.38** | 40 | 180 | **430** | 0.00 | 0.33 | **0.70** | 85 | 325 | **780** |
| Case 2 | 0.00 | 0.06 | **0.12** | 30 | 50 | **60** | 0.00 | 0.21 | **0.35** | 33 | 71 | **95** |

Table 1 shows the collision risk analysis of the on-ramp vehicle movements at different times. There is no collision risk in scenario 1 and scenario 2 as illustrated in Table 1. However, there is a lower risk in scenario 3 when the on-ramp vehicle attempting to merge on the main lane at time $t = 0.50s$. When the on-ramp vehicle merges on the main lane traffic, there is a significant collision risk at time $t = 0.75s$.

### C. PDRF ASSESSMENT

In this section, we evaluate the performance of the proposed model using the probabilistic driving risk field (PDRF) [54]. The PDRF aims to assess the kinetic collision risks associated with the on-ramp vehicle movement (trajectory) when the ORV attempts to merge on the main lane. The PDRF can be formulated as potential risks of collision using two different vehicle movements.

$$R_{MLV,ORV} = 0.5\mu^2 \left|\Delta V_{MLV,ORV}\right|^2 p_{MLV,ORV}. \tag{25}$$

where $R_{MLV,ORV}$ represents the kinetic PDRF values of the ORV. $\left|\Delta V_{MLV,ORV}\right| = |V_{MLV} - V_{ORV}|$ denotes the relative velocity difference between the MLV and the ORV. The $p_{MLV,ORV}$ represents the crash probability which ranges from 0 to 1, and $0.5\mu^2 \left|\Delta V_{MLV,ORV}\right|^2$ is the crash energy absorbed, at which the ORV collides with the MLV.

In traffic scenarios, we consider two vehicles: an on-ramp vehicle (ORV) and the main lane vehicle (MLV). Note that, we do not consider other vehicle (OV) in the traffic scenarios. Since it travels on its lane and does not pose threats to surrounding vehicles (see Fig. 7). We consider two different vehicle movements (trajectories) to determine the collision risks associated with them, as shown in Figs. 8 (c) and (d).

In the simulation, we set the lateral vehicle velocity of 1.5 m/s, and the total vehicle lane merging span time of 8 s. We considered two cases: (1) when the ORV traveling with the constant speed of $15m/s$ (case 1), and (2) the ORV traveling with the normal speed with the deceleration rate of $-1m/s^2$ (case 2). We evaluate the PDRF risks when the ORV merges with the main lane with different vehicle movements and time instances as illustrated in Fig. 9. The PDRF risk associated with the on-ramp vehicle movements in case 1 and case 2 at time $t = 0.5s$ (scenario 3) and $t = 0.75s$ (scenario 4) are illustrated in Fig. 9 (a) and Fig. 9 (b), respectively.

We can see from Fig. 9(a) that it has a lower crash probability and severity of the crash when the ORV attempt to merge on the main lane at time $t = 0.5s$, which indicate that there is a slight risks of collision between the ORV and MLV in this trajectory (see Fig. 7(c)) in terms of case 1, while there is no risk in case 2. While, when the ORV intersects with the MLV on the main lane at $t = 0.75s$. The crash probability and severity is much higher than the trajectory $t = 0.5s$, which clearly indicate that there is higher risks of collision in this trajectory (see Fig. 7(d)). In particular, the ORV should avoid merging on the on-ramp at time $t = 0.75s$, which may resulted in collision and crashes among vehicles.

Table 2 shows the PDRF analysis of the on-ramp vehicle movements by considering two different scenarios. We can see from Table 2 that the crash probability and severity of the on-ramp vehicle intersection on the main lane is far higher than the ORV attempting merging maneuver. This indicates that the PDRF effectively identifies the possibility of collision risks between the on-ramp vehicle and the main lane vehicle in both scenarios. It can be noted that, the probability and severity value increases as the on-ramp vehicle attempt to merge on the main lane traffic.

### D. PERFORMANCE EVALUATION BASED ON PATH PLANNING

In this section, we evaluate the performance of the proposed collision avoidance model using the path planning method based on the model predictive controller (MPC). The path planning exploits the MPC to determine the best path that the ORV takes while merging on the main lane without posing any collision risks to surrounding vehicles.

The vehicle model is needed in order to employ the MPC based path planning method and could be written as below.

$$\dot{\beta} = f\left(\beta\left(t\right), s\left(t\right)\right). \tag{26}$$

where $\beta\left(t\right)$ is the vehicle state variables, which can be represented as $\beta\left(t\right) = \left[\dot{x}, \dot{y}, \emptyset, \dot{\emptyset}, x, y\right]^T$ and $s\left(t\right) = [\sigma]$ is an input vector of the MPC.

The MPC could be used to obtain the best path for the ORV in terms of the objective function, as discussed in [55]. The objective function of the ORV collision-free path planning

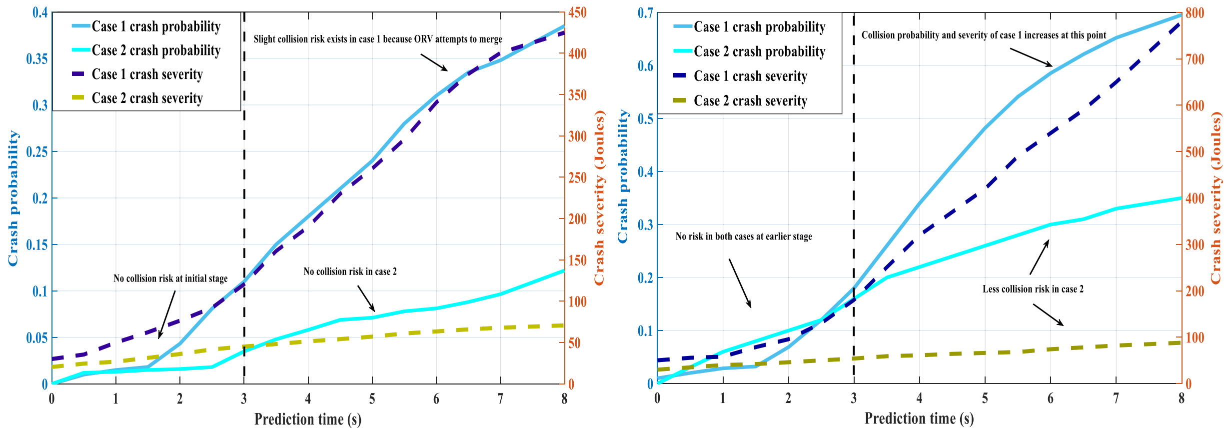



**FIGURE 9.** PDRF evaluation with different vehicle movements, (a) The ORV attempt to merge on the main lane at $t = 0.5$ $s$ and (b) ORV intersect with the MLV at $t = 0.75$ $s$.

based on the MPC can be written as below.

$$(\beta (t), s(t-1), \Delta S(t)) = \sum_{j=1}^{N_{pr}} \left\| y(t+j) - y_{orvref}(t+j) \right\|_{W_1}^2 + \sum_{j=1}^{N_{cr}} \| \Delta s(t+j) \|_{W_2}^2 . \quad (27)$$

where $N_{pr}$ and $N_{cr}$ denotes the prediction and control parameters, respectively. $w_1$ and $w_2$ are the weighting matrices. The first term indicates that the on-ramp vehicle follows a path that could avoid the collision with the main lane vehicle. While the second term is used to smoothly transition of the control vector.

In the simulation, we assume the MPC parameters in which the prediction and control parameters are $N_{pr}= 15$ and $N_{cr}= 10$, respectively. We aim to determine the effectiveness of the ORV planning velocity, which could not only avoid the collision risks with surrounding vehicles but also ensure the traffic and road safety by following the path. We assume that the velocity of the ORV is $20m/s$.

Fig. 10 shows the performance evaluation in terms of the longitudinal acceleration of the ORV and the velocity comparison of the ORV with path planning. From Fig. 10(a), we can see that the longitudinal acceleration of the on-ramp vehicle are within the constraint ranges. From Fig. 10(b), we can see that the ORV velocity path is more stable than the path planning model, indicating that the proposed model begins to control the ORV velocity when it merges on the main lane at on-ramp merging area, and subsequently mitigating the risks of collision with surrounding vehicles.

### E. A CASED STUDY WITH NGSIM TRAFFIC DATA

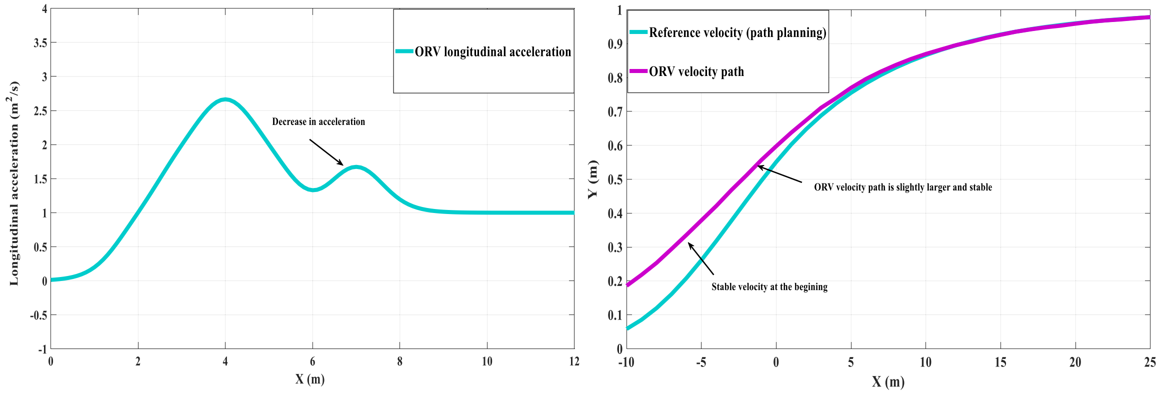
In this section, we evaluate the performance of the proposed model using the Next Generation Simulation Program (NGSIM) dataset [56]. The NGSIM traffic data are openly available to do the research in Transportation Engineering and to test accuracy of the developed Transportation models. The NGSIM program datasets consist of data collected from two freeways segments and two arterial segments using the high-resolution cameras, which record the vehicle positions at every 0.1 s.

The I-80 trajectory data were collected on the Interstate segment 80 (I-80) in Emeryville, California on April 13, 2005. The trajectory data consists of three different durations, such as from 4:00 pm to 4:15 pm, 5:00 pm to 5:15 pm, and 5:15 pm to 5:30 pm [56]. There are six lanes on the freeway segment of I-80, in which the lane 1 is the high-occupancy vehicle (HoV) lane and the lane 6 is the right-most lane (see Fig. 11), which has the on-ramp and off-ramp sections [56]. The data comprises of various traffic behaviors and patterns, and this study applies the data to validate the effectiveness of the proposed developed model based on the car-following behavior.

In order to solve the noise issue in the NGSIM trajectory data, the data was smoothed as discussed by Thiemann et al. [57]. The NGSIM I-80 trajectory data exhibits unrealistic velocity and acceleration spikes distributions. Therefore, the smoothing process needs to perform before analyzing the data and to ensure the accuracy of the model. We select the pairs of adjacent vehicles based on the selection criteria. First, we consider the leading and following vehicles are the passenger cars. Second, the on-ramp vehicle merges with the main lane vehicle at some point, and there is no other vehicle between them. The headway time between the leading and following vehicles is less than 5 s, and the headway distance between them is less than 50 m (164 ft.) [58].

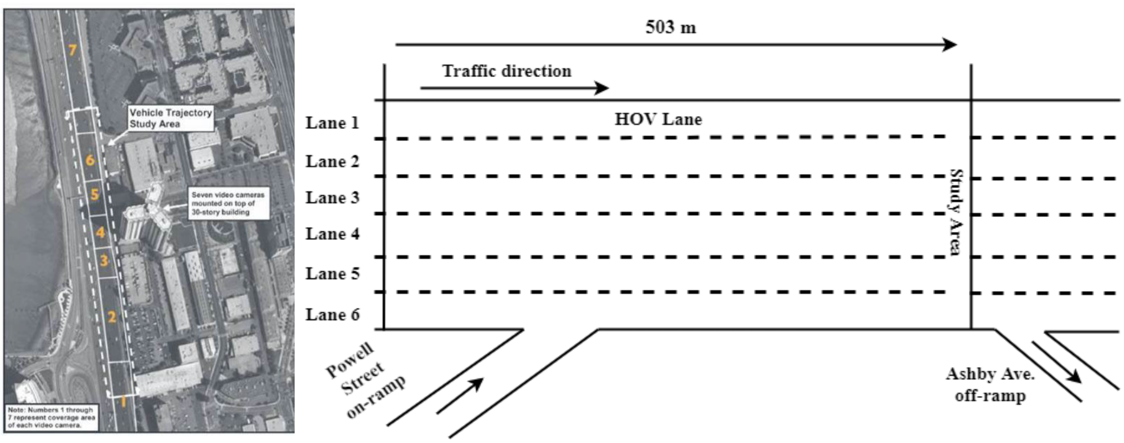
### F. COMPARISON OF MONTE-CARLO SIMULATIONS WITH NGSIM I-80 OBSERVATIONS

We considered the probabilistic distributions as inputs of conflicting merging interacting between vehicles, in order to perform the simulations using the Monte-Carlo model. We used the MATLAB R2018b to simulate the Monte-Carlo model. In the simulation, nearly 20,000 tests are performed in




(a) (b)

**FIGURE 10.** **(a) Results with different driving conditions, (a) longitudinal acceleration of the ORV and (b) velocity comparison of the ORV.**




(a) (b)

**FIGURE 11.** **Schematic representation for the I-80 trajectory data, (a) video coverage, and (b) study area [56].**

each scenario to obtain a useful insight into the Monte-Carlo model and the NGSIM I-80 traffic data. Note that we run the optimum number of simulation tests, which could provide adequate information, in order to compare the performance of the Monte-Carlo model with NGSIM traffic data.

The NGSIM I-80 traffic data provides the input sequences when vehicles interact at an on-ramp merging conflicting areas or when the on-ramp vehicle merges on the main lane. We considered two indicators (merging gap and merging headway), as discussed by Zhu and Tasic [59], in order to determine the successful merging process of vehicles. The results obtained from the proposed model at an on-ramp conflicting merging area based on the Monte-Carlo simulations compared with the NGSIM traffic dataset.

Fig. 12(a) shows the comparison between the results obtained from the Monte-Carlo simulations and the NGSIM data. We can see that the Monte-Carlo model could provide better distribution and insight of the on-ramp merging area (conflicting area). From Fig. 12(a), we can see that the ORV merges with the MLV on the main lane at about 3s. During this time, the MLV evasive response occurs when the ORV merges on the main lane. The results show that the NGSIM data are coincident with the Monte-Carlo model, indicating that the proposed method is able to identify the merging process between vehicles.

Similarly, Fig. 12(b) illustrates the comparison between the Monte-Carlo and the NGSIM data when both vehicles meet at conflicting merging areas. From Fig. 12(b), we can see that the estimating merging headway time is less than 3 s when both vehicles merge at an on-ramp conflicting region. This indicates that the MLV response occurs at 1 s and finishes around 3 s when the ORV vehicle arrives at the on-ramp merging point. When the merging point value is greater than 3 s, it is unlikely that the MLV evasive response occurs because the headway merging timing is greater than 3 s and the ORV already merges on the main lane. The results show that the merging events of the NGSIM traffic data agree well with the Monte-Carlo model, indicating that the ORV

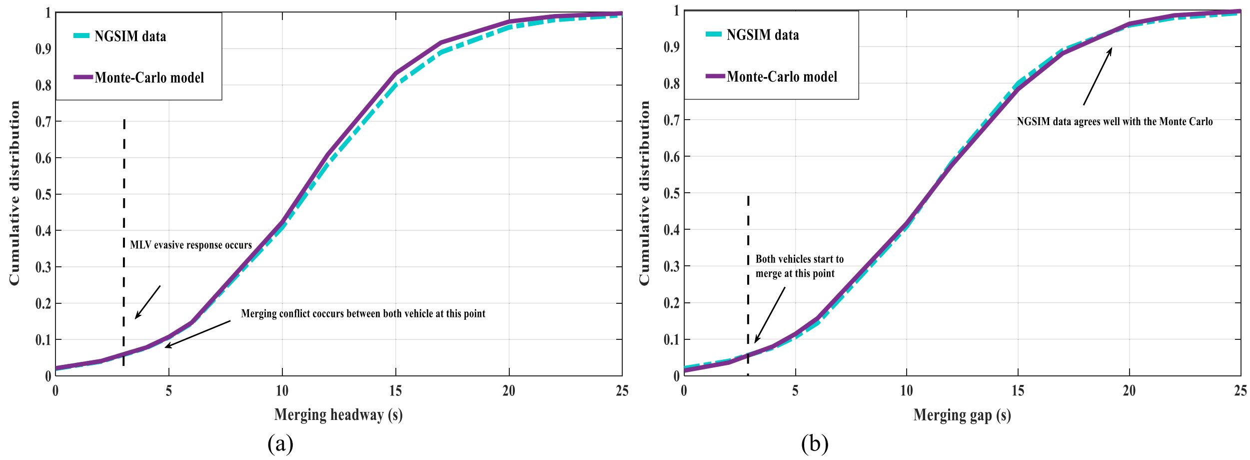



**FIGURE 12.** Monte Carlo model comparison with NGSIM data, (a) merge gap, and (b) merging headway.

successfully merges into the main lane using the real-time traffic data.

## VI. CONCLUSION

In this paper, we proposed a collision avoidance model incorporating different vehicle movements in merging areas. First, we introduced a decision-making algorithm that consists of a threat assessment model to assess the collision risks associated with different vehicle movements, such as when the ORV tries to merge on the main lane at $t = 0.5s$ and when the ORV intersects with the MLV at $t = 0.75s$, and to avoid collisions based on the safe lateral and longitudinal acceleration of the ORV in merging areas. Second, we evaluated the evasive response of the MLV to the aggressive merging behaviors of the ORV. The MLV applies the brake to maintain a sufficient distance from the ORV and to avoid the collision risks when the initial headway between them is small. Third, we applied a vehicle stabilization mechanism that uses a stable envelope that limits the states of main lane vehicle within the envelope. This can stabilize the vehicle and prevent it from colliding with other vehicles or objects. The simulation results verify the effectiveness of the proposed CA model and illustrate that the model can accurately estimate the collision risks associated with the different on-ramp vehicle movements and has the ability to improve traffic and road safety. Furthermore, we have evaluated the performance of the proposed model using the NGSIM I-80 trajectory dataset. The findings show that the proposed model can be useful for avoiding collisions in real-time scenarios.

One of the limitations of this study is that it did not consider the complex interaction between the main lane vehicle and other vehicles. Such an examination could be useful for implementing the collision risk model in real-time. Therefore, it is necessary to incorporate the scenario in the future model to determine the risk level and severity associated with them. In addition, we did not consider the traffic controller (traffic lights) to evaluate the proposed collision avoidance model, which could provide better insight and would help to implement the model in real-world scenarios. These limitations will be addressed in our future research.

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