IEEE Access
Multidisciplinary : Rapid Review : Open Access Journal

Received 5 July 2023, accepted 30 August 2023, date of publication 4 September 2023, date of current version 14 September 2023.

Digital Object Identifier 10.1109/ACCESS.2023.3312028

RESEARCH ARTICLE

Analysis and Modelling of Passing Sight Distance Using Vehicle Dynamic Response

ABHISHEK RAJ[1], PARTH DESHPANDE[2], (Graduate Student Member, IEEE), BHARGAVA RAMA CHILUKURI[1], AND SHANKAR C. SUBRAMANIAN[3], (Senior Member, IEEE)

[1]Department of Civil Engineering, Indian Institute of Technology at Madras, Chennai 600036, India
[2]Department of Engineering, University of Cambridge, CB2 1PZ Cambridge, U.K.
[3]Department of Engineering Design, Indian Institute of Technology at Madras, Chennai 600036, India

Corresponding author: Abhishek Raj (ce19d700@smail.iitm.ac.in)

This work was supported in part by the Ministry of Education, Government of India, through the Prime Minister Research Fellowship (PMRF) Scheme; and in part by the Ministry of Skill Development and Entrepreneurship, Government of India, under Grant EDD/14-15/023/MOLE/NILE.

ABSTRACT Passing Sight Distance (PSD) is pivotal for two-lane undivided highways, impacting their safety and operational performance. However, current PSD standards and models are based on simplistic assumptions and do not consider road characteristics and vehicle dynamic response. This study investigates the adequacy of PSD models in practice by comparing them with more realistic values obtained from IPG CarMaker®, a commercial vehicle and traffic simulation software. Similar test variables are chosen to compare the simulation and standards consistently. Since road gradient and road-tire friction affect the acceleration capabilities of vehicles, their effects on PSD are analysed by configuring the parameters in the simulation. High deviations of up to 94% are observed in the PSD values compared to the existing model under different road conditions. In the paper's second half, the existing model is evaluated for its performance in mixed traffic conditions by comparison with empirical data. Followed by this, an analytical model for PSD is proposed, which considers vehicle dynamic response. This model allows parameter selection and the application of physical vehicle constraints, considering the microscopic behaviour of a vehicle during an overtake. The deviations observed in PSD values obtained from this model are within 5% for the specified test cases simulated in the vehicle dynamics simulator. Furthermore, the model is benchmarked against existing models using field data, demonstrating its superior performance in terms of feasibility and safety. The accurate replication of overtaking manoeuvres by the analytical model will have significant implications for geometric design, traffic operations, advanced driver assistance, autonomous vehicle applications and policymaking.

INDEX TERMS Passing sight distance, trajectory modelling, two-lane highways, vehicle dynamics simulation.

I. INTRODUCTION

The percentage share of fatalities due to head-on collisions increased from 16.3% in 2017 to 19.2% in 2020 in India [1], [2]. These crashes also constitute a significant share of 10.1% of all accidents in the US [3]. The risk of a head-on collision is maximum in the case of two-lane undivided highways, which make up a major proportion of the road network around the globe. These roads represent more than 90% of the highway network in the USA, 90% of all rural roads in Germany, and around 92% of all roads in Spain [4], [5]. In India, they make up around 50% of the national highway network [5], [6]. Overtaking is a complicated manoeuvre that frequently occurs on two-lane undivided highways, which has significant implications for the safety of road users. A fast-moving vehicle tries to pass a slower-moving vehicle ahead by using the adjacent lane, which is reserved for opposing traffic. The longitudinal distance along the road that a driver

The associate editor coordinating the review of this manuscript and approving it for publication was Leandros Maglaras.

should be able to see for safely completing the manoeuvre is commonly referred to as the Passing Sight Distance (PSD) in literature [7].

Therefore, adequate PSD provision along the highway is critical for safe manoeuvring. Moreover, the inability of fast-moving vehicles to pass slow-moving vehicles due to inadequate PSD can lead to slow-moving bottlenecks or queues. This reduces the facility's average speed, and the service level deteriorates consequently [7]. Most global research towards developing and modifying PSD standards began in the pre-millennium era [7]. These models were primarily based on field data collected during the 1970s-80s in homogeneous traffic conditions [8], [9], [10], [11]. Glennon's model is one of the seminal analytical models widely used in PSD design and practice [11], [12]. However, this model makes several assumptions to develop mathematical relationships for PSD. Also, the core framework of this model is solely based on kinematics and does not consider vehicle dynamics and empirical driving data. In the present context, state-of-the-art vehicles have improved acceleration capabilities, higher power-weight ratios, and updated aerodynamic designs. Secondly, driving behaviour has evolved over the years due to the upgradation of road infrastructure and socio-economic changes. Consequently, aggressive manoeuvres have become prevalent in recent years due to increased traffic congestion, time pressure and impatience. Nevertheless, PSD design has not been revised since the 1990s to include these advancements in vehicular technologies and evolved driving behaviour.

Moreover, researchers have not sufficiently focused on the effect of road and environmental parameters on overtaking. In hilly areas connected by two-lane undivided highways, the gradient is essential for designing PSD [13]. Moreover, climatic conditions affect the tire-road friction, which has further implications on the acceleration capability of a vehicle during a passing manoeuvre [14]. Visibility conditions also affect how drivers initiate and perform an overtake [14]. While some studies have examined the effect of these parameters on PSD, their examination was limited to specific parameters, motivating the need for a systematic and comprehensive investigation.

Thus, there is an evident need to revisit the PSD standards in light of the improved vehicular design, evolved driving behaviour, and road and environmental parameters. The objectives of this study are three-fold:

- Evaluate PSD values using a vehicle dynamics simulation under various road and vehicle characteristics scenarios.
- Evaluate the existing model's performance against the simulation results and using empirical data.
- Proposal of an analytical model based on vehicle dynamics for PSD design and assess its performance using empirical data.

Simulations are performed with similar kinematic variables such as speeds, speed differentials, and roadway design parameters in IPG CarMaker®, a vehicle simulation software. The simulation results are compared with the existing standards, and the discrepancies are discussed. Furthermore, empirical data collected on a two-lane highway was used to benchmark the existing and proposed analytical models' performance.

By achieving these objectives, we aim to contribute to both research and application. In terms of research, our proposed model advances the field of overtaking models by incorporating vehicle and roadway parameters to provide generalizability. Consequently, researchers can use the model as a reliable framework for analysing and predicting overtaking behaviour and PSD for various situations. In terms of application, the model will contribute to upgraded roadway infrastructure design. Road designers can use the proposed model to calculate appropriate and accurate PSD. This can be done by providing additional passing zones and improving visibility, thereby enhancing safety. Furthermore, traffic engineers can implement the model to optimise traffic flow in congested sections with low service levels. The study can also find potential applications in advanced driver assistance systems (ADAS), where the model can be integrated with controllers. Traffic conditions and road geometry can be analysed using the sensors mounted on the vehicle. This can be used to issue overtaking alerts to drivers, assisting them in making safer overtaking decisions.

The rest of this paper is organised as follows. The following section presents a review of the literature on existing models for PSD. In the subsequent two sections, the PSD values calculated from Glennon's model are compared with values obtained from IPG CarMaker® followed by benchmarking of Glennon's model with empirical data on overtaking manoeuvres. Post this, an analytical methodology for calculating PSD based on a trajectory with vehicular and driver constraints is proposed in the next section, along with a final section for concluding remarks and recommendations for future research.

II. LITERATURE REVIEW

One of the first sets of standards to define PSD requirements for two-lane highways was published in "*A Policy of Geometric Design of Rural Highways*" [15] by the American Association of State Highway Officials (AASHO[1]). This was primarily based on field data of passing manoeuvres collected during the late 1930s. The policy determined the minimum PSD [7] as

$$\mathrm{PSD} = d_1 + d_2 + d_3 + d_4, \tag{1}$$

where d_1 is the longitudinal distance travelled during the driver's perception-reaction time and acceleration to the point of encroachment of the opposing lane, d_2 is the longitudinal distance travelled by the passing vehicle in the opposing lane, d_3 is the clearance longitudinal distance between the passing vehicle and oncoming vehicle after the passing manoeuvre is

[1]American Association of State Highway and Transportation Officials (AASHTO) was known as AASHO, before 1973.

completed, and d_4 is the longitudinal distance travelled by the oncoming vehicle for two-thirds of the passing distance [16].

The Manual on Uniform Traffic Control Devices (MUTCD) presented criteria for marking the passing and no-passing zones, considerably lower than the AASHO criteria [7]. One of the limitations of this criterion was that it failed to provide a mathematical rationale for deriving PSD values. Various authors later critiqued the AASHO and MUTCD design values for their conservative nature, simplistic assumptions, and use of obsolete data [7]. The following subsection discusses the subsequent studies while grouping them based on their similarities and differences.

A. CRITICAL POSITION MODELS

Several alternative models were developed from the 1970s to the late 1990s based on the critical position (CP) concept to estimate PSD. The CP is defined as a point in the time-space domain during the overtaking manoeuvre, after which the driver cannot abort safely to prevent a collision. Van Valkenburg and Michael introduced CP [8] and defined it by comparing the bumper positions of the passing and passed vehicles. It was extended further as a point where the time to abort the pass is the same as the time to complete it [9]. It was later argued that CP could be explained more logically by equating sight distances for abortion and completion of a pass [10], rather than temporal comparison [9]. Consequently, several studies used sight distance for analysing CP [11], [17], [18], [19], [20], [21].

A review of alternative PSD models found that the models proposed by Glennon [11] and Hassan et al. [21] most adequately represent the PSD needs of passing drivers [7]. The reasonable argument that the likelihood of a passing manoeuvre getting aborted was high at the start of a pass was supported by both these models. Besides this, both the models accounted for the trade-off between the completion and abortion of a pass to derive the PSD values that were not as conservative as AASHTO. Subsequently, CP based on sight distance was applied to compute PSD for the geometric design of two-lane highways in the latest AASHTO *Green Book* [12]. The overtaking process concerning CP is described in Fig. 1. Moreover, a recent study implemented Glennon's model to compute the PSD required for passing a truck platoon [22].

B. RECENT OVERTAKING STUDIES

After the proposal of CP-based models, the focus of researchers shifted to using field data for PSD computation. This was driven by technological advancements in the late 1990s, which enabled easier data collection and extraction. Polus et al. [23] quantified the components of PSD using field data collected in Israel and found AASHTO standards to be slightly conservative. A later study in Spain reaffirmed this [24], which found the PSD components given by AASHTO to be higher than field observations. Recent studies have aimed to analyse the factors which influence the

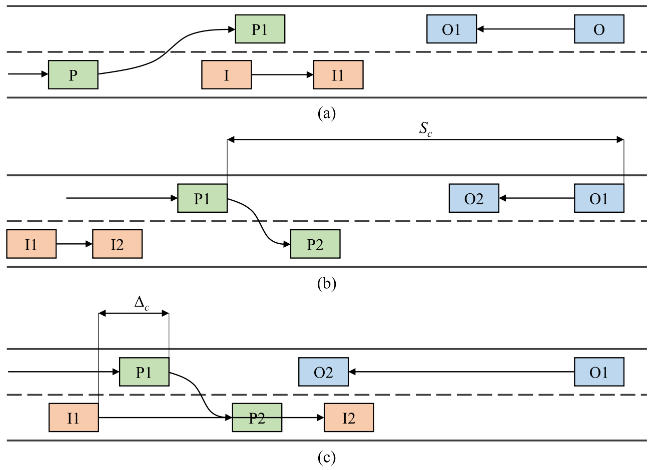


FIGURE 1. Passing mechanism based on critical position concept. (a) The first phase of passing. (b) Completed manoeuvre from the critical position. (c) Aborted manoeuvre from the critical position. P - passer, I - impeding vehicle, O - oncoming vehicle.

overtaking behaviour of drivers. It was found that the speed of passing and impeding vehicles [25], distance to opposing vehicle [26], traffic volumes [27], and road gradients [28] influence the overtaking behaviour of drivers. Other studies have attempted to quantify the risk involved in overtaking manoeuvres [27], [29]. Studies showed that an increase in the size of impeder [29], the lower speed difference between passer and impeder [29], and higher traffic volumes [27] may elevate the risk in overtaking manoeuvres. A summary of these studies and CP-based models is presented in Table 1.

Much of the research on developing PSD models and standards was done in the pre-millennium era, in which several restrictive assumptions were made for speed differential, acceleration, and headways. Moreover, most works considered only vehicle length for modelling PSD while neglecting crucial vehicle parameters such as weight distribution, steering limit and comfortable acceleration [11], [19], [20], [21]. Although some recent studies have utilised empirical data [5], [22], [33], [34], their focus has primarily been on providing PSD estimates rather than developing generalisable overtaking models that can be applied across different situations to compute PSD. Also, despite advancements in vehicular technologies, there has been no systematic attempt to incorporate vehicle dynamic response in recent studies. Finally, PSD modelling by researchers has overlooked the effect of roadway factors such as friction. Although road gradient has been analysed for a fixed speed limit of 70 km/h [28], the effect of varying speeds on overtaking manoeuvres should have been addressed. These roadway factors influence the acceleration and deceleration of a vehicle during overtaking manoeuvres, thereby affecting the PSD requirements of drivers. These identified gaps highlight the need for developing an adaptable overtaking model that incorporates insights from empirical data, vehicle, and roadway parameters to provide accurate estimates of PSD.

While field data can provide insights into real-world overtaking behaviour, the absence of vehicle-dynamics-based

TABLE 1. Review of PSD models and studies.

Study	CP defn.	Speed diff.	Acln.	Road grade	Fric.	Vehicle lengths	CA & SL	Lateral motion	Remarks
[8]	BP	C	-	×	×	×	×	×	Introduced CP concept, failed to find CP analytically.
[9]	T	V	-	×	×	×	×	×	Variable speed differential, Logical flaw in CP definition.
[10]	SD	C	-	×	×	×	×	×	Adequate CP definition, Quantification of CP absent.
[17]	SD	C	V	×	×	×	×	×	Mathematical relationship for CP; inclusion of performance capabilities in PSD computation.
[11]	SD	V	C	×	×	✓	×	×	Replication of actual manoeuvre, Trade-off between completed and aborted manoeuvre.
[19]	SD	C	V	×	×	✓	×	×	Extension of the work by [11] for trucks.
[20]	SD	C	V	×	×	✓	×	×	Studied effect of trucks, constant speed differential.
[21]	SD	V	-	×	×	✓	×	×	Revised model based on shortcomings of previous models.
[23]	-	V	C	×	×	✓	×	×	PSD quantification based on field data.
[30]	BP	V	-	×	×	×	×	×	Empirical modelling of passing distance and duration based on traffic and driver features.
[31]	-	C	-	×	×	×	×	×	Studied passing manoeuvres on rural roads to validate existing design model.
[32]	-	V	-	×	×	✓	×	×	Investigated the effect of speed of impeder and PSD on driver behaviour during overtaking manoeuvres.
[33]	-	V	-	×	×	×	×	×	Multiple linear regression model based on headways and speeds of passer and impeders.
[28]	-	V	V	✓	×	✓	✓	×	Studied the passing of a single truck and truck platoon by car considering vehicle dynamic constraints.
[22]	SD	V	C	×	×	✓	×	×	Application of model developed by [11] to estimate PSD for truck platoons, followed by validation in VISSIM.
[5]	BP	V	C	×	×	✓	×	×	Developed models to provide estimates of overtaking distance for passenger cars overtaking other vehicle classes.
[27]	-	V	V	×	×	✓	×	×	Quantification of risk at the end of overtaking manoeuvres using a combined simulation approach.
[25]	-	C	V	×	×	✓	×	×	Estimated PSD for different vehicle classes and developed a model to predict the passing probability.
[29]	-	V	-	×	×	✓	×	×	Developed discrete choice models to quantify the conflict risk severity during overtaking manoeuvres.
This study	SD	V	✓	✓	✓	✓	✓	✓	Evaluation of parameters affecting PSD; proposal of an analytical model for overtaking manoeuvre.

CP: critical position, Acln.: Acceleration, Fric.: Tire-road friction, , CA: comfortable acceleration, SL: steering limit, BP: bumper position, T: time, SD: sight distance, C: constant, V: variable, PSD: passing sight distance

models may limit our comprehension of the overtaking manoeuvre. To address these gaps in the literature, this study evaluates the adequacy of PSD standards in practice with results obtained from test runs in IPG CarMaker® (IPG-CM), a vehicle dynamics simulation software. The effects of road gradient and tire-road friction on PSD are investigated. Furthermore, the existing model is evaluated using empirical data on overtaking manoeuvres. Finally, an analytical model is proposed, which considers the microscopic behaviour of a vehicle for determining the PSD requirements.

III. GLENNON'S MODEL

Glennon derived a mathematical equation to find CP and critical PSD values using the trade-off between aborted and completed passes [11]. The following are the major assumptions of the model:

1) Passenger cars (of length 16 ft) were chosen as passing and impeding vehicles similar to AASHTO.
2) Existence of a critical point in the passing manoeuvre based on sight distance.
3) A constant deceleration rate of 8 ft/s^2 during an abortion.
4) A variable speed differential over a constant value as in AASHTO.
5) A constant headway of 1 second between the passer and impeder at the end of the pass.

This study used these equations to determine the PSD requirements for pre-determined speeds. The speed differential (m) between the passing and passed vehicles was interpolated from Glennon's work [11]. This was done to ensure a consistent comparison between the results from Glennon's model and the simulation. The CP (Δ_c) and the critical PSD (S_c) are calculated in Glennon's model as [11]:

$$\Delta_c = L_p + m\left[\frac{(2G+L_i+L_p)}{2v-m} - \sqrt{\frac{4v(2G+L_i+L_p)}{d(2v-m)}}\right], \quad (2)$$

$$S_c = 2v\left[2 + \frac{L_p - \Delta_c}{m}\right], \quad (3)$$

where v and m are the design speed and speed differential between the passer and impeder, respectively. L_p and L_i represent the lengths of the passer and impeder, respectively. d signifies a safe deceleration rate for the abortion of a pass. G indicates the clearance gap between the passer and the impeder at the end of the pass. Due to the assumed headway of 1 s, G becomes equal to m. It is evident from (2) that the position of the critical point depends on the speeds and lengths of both the passing and the passed vehicles. The critical PSD, S_c, is computed using (3) once the position of the

TABLE 2. PSD values from Glennon's model.

Speed of Passer (v, km/h)	Speed differential (m, km/h)	Critical Position (Δ_c, m)	Critical PSD (S_c, m)
40	20.14	-15.3[a]	121.1
50	19.14	-14.8	153.8
60	18.14	-14.0	185.4
70	17.14	-12.9	216.1
80	16.14	-11.9	246.0
90	15.14	-10.7	275.1
100	14.14	-9.6	303.4

[a]Negative sign indicates that the critical position occurs behind the impeder (in the opposite direction of its movement.)

critical point is known from (2). The pre-determined speed range is chosen to vary from 40-100 km/h. The lengths of the passing and impeding vehicles are chosen for two present-day vehicles, identical to the ones chosen in the simulation. The PSD values obtained using Glennon's model [11] are shown in Table 2.

As seen in Table 2, the critical position shifts ahead with an increase in the speed of the passer. The increase in PSD is almost linear with the passing vehicle's speed, as evident from (3). As suggested by AASHTO [35], these are minimum PSD values used in the design of two-lane undivided highways, which may not be sufficient for passes under certain conditions.

While the derivations by Glennon attempt to replicate the manoeuvre, the model suffers from several limitations: (1) Plugging in $(L_p - \Delta_c)/m$ from equation 2 into equation 3 indicates that PSD depends upon the sum of passer and impeder's length, which may occlude the effect of one vehicle class passing other and vice versa, (2) The vehicle is assumed to slow down to unreasonably low speeds in case of pass abortion, which impeder's speed should logically constrain, and (3) Assuming a fixed deceleration rate (2.43 m/s^2) for all speeds is not rational in the present context, as modern vehicles are capable of decelerating faster (up to 4 m/s^2 [36]) and safely due to advanced braking systems. Besides, acceleration capabilities are affected considerably by road parameters such as gradient and friction. Although it has been well established that dynamic models perform better for high-speed scenarios such as overtaking [37], [38], Glennon's kinematic model limits its use cases to low speeds from a vehicular perspective. So, to evaluate the adequacy of Glennon's model for current conditions, the values obtained from Glennon's model are compared with those from IPG-CM to investigate the effect of various vehicle and road parameters, the details of which are discussed next.

IV. OVERTAKING SIMULATION IN IPG-CM

The first step in analysing the existing PSD models is to compare their estimates with values for specific pre-determined test cases using IPG CarMaker® (IPG-CM), a software for vehicle dynamics and traffic simulation. IPG-CM is an open integration and testing platform that helps visualise virtual test runs. It provides adaptable models for vehicles, roads and traffic. Several studies have demonstrated IPG-CM to

TABLE 3. Pre-defined simulation parameters.

Parameters	Notation	Value (Units)
Number of lanes	n_l	2
Lane width	y_l	3.500 m
Wheelbase of passer	l	2.55 m
Distance of Centre of Gravity of passer from front axle	l_f	1.005 m
Distance of Centre of Gravity of passer from rear axle	l_r	1.545 m
Curb weight of passer	M	1,085 kg
Front tyre cornering stiffness of passer (each tyre)	C_f	83130.4 N/rad
Rear tyre cornering stiffness of passer (each tyre)	C_r	83130.4 N/rad
Length of passer car	l_P	3.989 m
Length of impeder car	l_I	4.129 m
Power rating of the passer	P_p	89 hp

TABLE 4. Calibrated parameters.

Parameters	Notation	Value (Units)
Minimum speed difference	v_{min}	10 km/h
Minimum time headway	h_{min}	1 s
Minimum following gap	g_{min}	$(v-m)$ m
Maximum longitudinal acceleration	a_{max}	4 m/s^2
Energy-efficient driving[b]	EED	0.75
Overtaking rate of IPGD	O	1

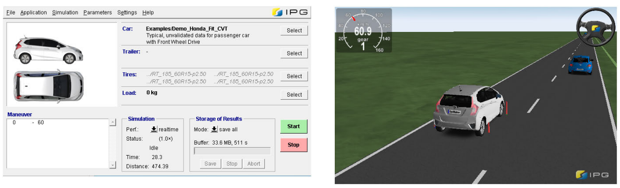
[b]Energy efficient driving is a dimensionless parameter that lies between 0 and 1, and is used to optimise the fuel usage during driving [42].

accurately replicate dynamic vehicle characteristics such as lateral acceleration and longitudinal speed [39], [40], [41]. This substantiates the use of IPG-CM as a reliable simulation tool. IPGDriver® (IPGD), an in-built configurable simulation driver, is used to record the properties of overtaking manoeuvres for these test cases [42]. A glimpse at the interface of CarMaker® 8.1 is shown in Fig. 2. The following steps are involved in the initial setup for the simulation runs. First, the speeds and initial locations of the passing, impeding, and oncoming vehicles are provided to IPG-CM via the manoeuvre and traffic interfaces. The length of the road stretch, lane width, number of lanes, friction properties, and gradient are set in the road parameters interface. The driving style is configured using variables such as energy efficiency and overtaking rate in the IPGD interface [42]. The overtaking rate[2] is set to its highest value of 1 to ensure that all possible passing manoeuvres are captured in the data. The PSDs for different manoeuvres are obtained from IPG-CM by setting up simulation test runs with the parameters shown in Table 3 and Table 4.

A. SIMULATION METHODOLOGY

The critical point needs to be measured for each test case to find the critical PSD. Here, the critical point has been defined as the last position of the passer in reference to the impeder when it has the option of either completing the

[2]The overtaking rate is a dimensionless parameter which lies between 0 and 1, and is used to quantify the likelihood of doing an overtake [42].



(a) (b)

FIGURE 2. The IPG CarMaker® environment for vehicle and traffic simulation. (a) Initial screen with options for configuring simulation parameters. (b) IPGMovie® interface for visualising vehicle manoeuvres in real-time.

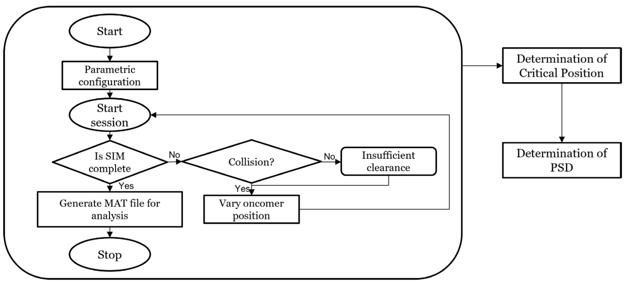


FIGURE 3. Simulation workflow in IPG-CM to compute CP and PSD.

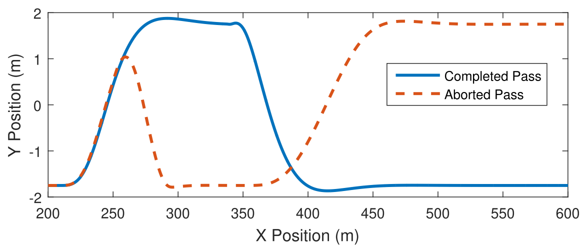
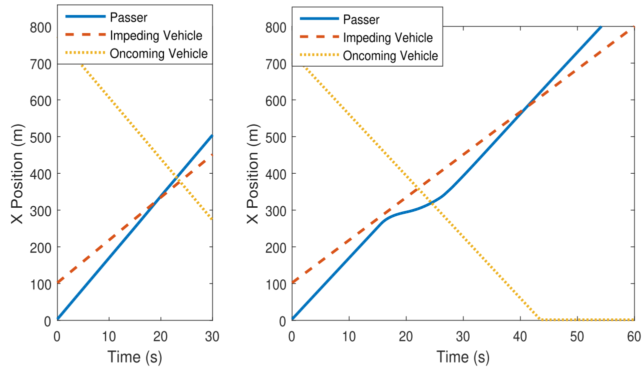


FIGURE 4. Vehicle trajectories from IPG-CM for finding the critical position with completed and aborted manoeuvres.

passing manoeuvre or aborting it while it is in the adjacent lane. If the passer senses the oncoming vehicle after it has crossed the critical position, it would not be able to abort the manoeuvre safely and would try to complete it. On the other hand, if it senses the oncoming vehicle before the critical position, the manoeuvre would be aborted. To find the critical position experimentally, the initial position of the oncoming vehicle is varied, and the overtaking behaviour is recorded. As the oncoming vehicle is brought closer, there occurs a point at which the passer switches from completing the manoeuvre to aborting it. At this point, the longitudinal distance between the passer and the impeding vehicle is recorded as the critical distance, Δ_c, and the longitudinal distance between the passer and the oncoming vehicle is the PSD, S_c. The overall simulation workflow has been demonstrated in Fig. 3. The trajectories of the passing vehicle for aborted and completed manoeuvres are shown in Fig. 4. Fig. 5 shows the time-space diagrams of the vehicles for aborted and completed manoeuvres in the IPG-CM simulations for two different initial positions of the oncoming vehicle used for finding the critical position.



(a) (b)

FIGURE 5. Time-space diagrams of all vehicles from IPG-CM for (a) completed pass and (b) aborted manoeuvre and reattempted pass.

The results of the test runs are shown in Table 5, which indicates that Glennon's model has high deviations from the IPG-CM PSD values, up to 94% at high speeds. An opposite trend for the critical positions is observed in Glennon's Model and IPG-CM. In the case of IPG-CM, the critical position advances with an increase in the passer's speed. This trend of the critical position advancing with an increase in speed seems more reasonable, as drivers practically tend to maintain a larger clearance from the impeding vehicle ahead at higher speeds while deciding to pass. Higher relative speeds between the passing and oncoming vehicles also demand a larger gap to abort at high speeds safely. These observations show the inadequacy of PSD standards based on Glennon's model. The difference is attributed to IPGD's preference for maintaining sufficient clearances from the impeding and oncoming vehicles when the pass is completed or even aborted. Alongside this, the IPGD ensures no loss of control when manoeuvring, thus choosing to perform only safe and feasible manoeuvres. These results agree with previous studies, where AASHTO standards were found to be inadequate for passing manoeuvres of cars [23], [33].

TABLE 5. PSD values from IPG CarMaker®.

Speed of Passer (v, km/h)	IPG-CM's CP (Δ_c, m)	Glennon's PSD (S_c, m)	IPG-CM PSD (S_c, m)	Difference in PSD values (%)
40	-14.4	121.1	159.0	31.3
50	-18.0	153.8	197.3	28.3
60	-21.6	185.4	258.1	39.2
70	-22.7	216.1	296.6	37.3
80	-26.1	246.0	396.0	61.0
90	-28.7	275.1	531.6	93.2
100	-29.8	303.4	588.2	93.9

B. EFFECT OF ROAD GRADIENT

The frequency and length of passing sections are low in steep gradients to reduce construction costs, thereby reducing the feasibility of safely completing an overtake. Moreover, the operational efficiency of logistic movement to remote areas suffers due to lower average speeds [43]. AASHTO [35] points out the effect of gradients on PSD requirements but fails to quantify the same. Therefore, the effect of gradient on PSD is studied in this work. However, negative gradients are not studied because passing becomes convenient for a vehicle moving downgrade as it can accelerate quickly, and the opposing vehicle moves slowly [35]. In contrast, during acceleration on positive gradients, the tires' capabilities change due to a dynamic load shift from the front to the rear wheels. Therefore, positive gradients require consideration as the load on the passer's powertrain increases, impacting its acceleration capability [13]. Hence, simulations are performed in this study for three cases to investigate the effect of road gradients on PSD values.

Three gradient levels that represent different terrains, 2.5% (plain), 5% (rolling), and 6% (mountainous), are studied in this research. The results of the simulations are shown in Table 6. Compared to PSD results obtained using Glennon's model, the PSD values are significantly higher. The deviation ranges from 22% at lower speeds to as high as 49% at higher speeds, indicating an underestimation of PSD by Glennon for different gradients. Also, the PSD value increases marginally with higher gradients. To conclude the impact of varying gradient levels on PSD, a student's t-test was conducted with the PSD values obtained from IPG-CM at speeds varying from 40 km/h to 100 km/h on different grades with that from flat terrain. The null and alternative hypotheses formulated are:

- H_o: No significant difference exists between the PSD obtained at higher grades compared to flat terrain.
- H_a: A significant difference exists between the PSD obtained at higher grades compared to flat terrain.

The test statistics were obtained for the three gradient levels as $t_{stat,2.5\%} = 3.10$, $t_{stat,5\%} = 3.48$, $t_{stat,6\%} = 4.04$, and $t_{crit}(0.05, 6) = 2.45$. Lower t_{crit} values compared to t_{stat} values present evidence to reject H_o, indicating a significant difference between the PSD values obtained at different grades and those from flat terrain. This is rational, as a gradient can impact the overtaking ability of a car. While driving on a positive grade, the accelerating capability of the passer reduces due to gravitational resistance, and it takes longer to gain sufficient speed to complete the manoeuvre. This results in prolonged overtaking time and distance for the passing vehicles. Therefore, it becomes essential to include road gradients as a parameter in PSD design.

C. EFFECT OF ROAD-TIRE FRICTION

Road-tire friction is crucial in controlling the movement and stability of a vehicle. To determine the effect of road-tire friction, three values of friction coefficient, 0.8 (dry), 0.6 (wet), and 0.2 (icy) are studied. The PSD values obtained from the simulation for the specified road friction levels are shown in Table 7. The values deviate from Glennon's PSD by 20% at lower speeds to 52% at higher speeds, indicating an underestimation of PSD by Glennon for different friction levels. Moreover, PSD values are high (low) at low (high) friction levels. To conclude the impact of friction levels on PSD, a student's t-test was conducted with PSD values from IPG-CM at speeds from 40 km/h to 100 km/h on wet and icy surfaces with that on dry surfaces. The null and alternative hypotheses formulated are:

- H_o: No significant difference exists between the PSD obtained at wet and icy surfaces compared to dry surfaces.
- H_a: A significant difference exists between the PSD obtained at wet and icy surfaces compared to dry surfaces.

The test statistics for friction levels of 0.2 and 0.6 were obtained as $t_{stat,0.2} = 9.57$, $t_{stat,0.6} = 9.72$, and $t_{crit}(0.05, 6) = 2.45$. Lower t_{crit} values compared to t_{stat} values present evidence to reject H_o, indicating a significant difference between the PSD values for wet and icy surfaces compared to dry surfaces. This is logical since road friction influences the accelerating capability of a vehicle. Drier roads with high friction provide a greater grip to the tires, allowing the vehicle to accelerate quickly and complete the manoeuvre. Furthermore, the responsiveness of the vehicle steering is enhanced at higher friction, which causes prompt tire reaction to steering inputs. On the contrary, lower friction levels can decrease the grip and deplete the accelerating capability, leading to prolonged overtaking times. Thus, surface friction can impact the overall safety of the manoeuvre, indicating the need to include road-tire friction in PSD design.

TABLE 6. PSD values from IPG CarMaker® for varying gradients.

Speed of Passer (v, km/h)	Glennon's PSD (S_c, m)	IPG-CM's PSD at different grades (S_c, m)			
		0%	2.5%	5%	6%
40	121.1	159.0	159.2	159.4	159.5
50.0	153.8	197.3	197.5	197.6	197.8
60.0	185.4	258.1	258.3	258.7	259.1
70.0	216.1	296.6	296.9	297.3	297.5
80.0	246.0	396.0	396.4	396.9	397.3
90.0	275.1	531.6	532.0	532.8	533.2
100.0	303.4	588.2	589.5	590.8	591.3

TABLE 7. PSD Values from IPG CarMaker® for varying road friction.

Speed of Passer (v, km/h)	Speed differential (m, km/h)	Glennon's PSD (S_c, m)	Critical PSD from IPG-CM (S_c, m)		
			$f = 0.2$	$f = 0.6$	$f = 0.8$
40	20.14	121.1	176.4	168.7	159.0
50	19.14	153.8	220.1	209.2	197.3
60	18.14	185.4	283.2	270.3	258.1
70	17.14	216.1	332.9	313.5	296.6
80	16.14	246.0	428.6	413.9	396.0
90	15.14	275.1	562.9	551.3	531.6
100	14.14	303.4	632.2	610.6	588.2

V. BENCHMARKING WITH EMPIRICAL DATA

To evaluate how closely Glennon's model replicates the overtaking behaviour in the field, the trajectories obtained from

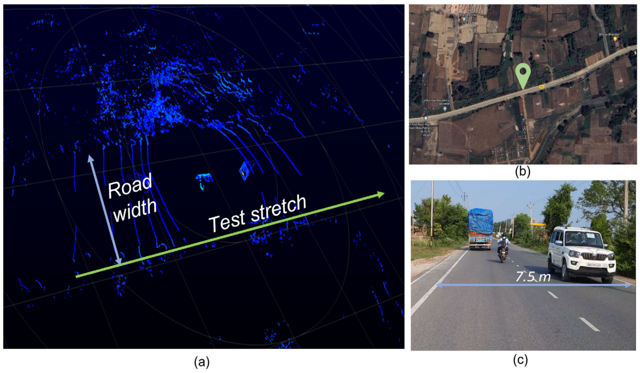


FIGURE 6. (a) 3-D point cloud of the roadway environment generated by LIDAR, (b) Data collection site - NH 922 marked in Google Maps, (c) On-ground view of the two-lane undivided highway.

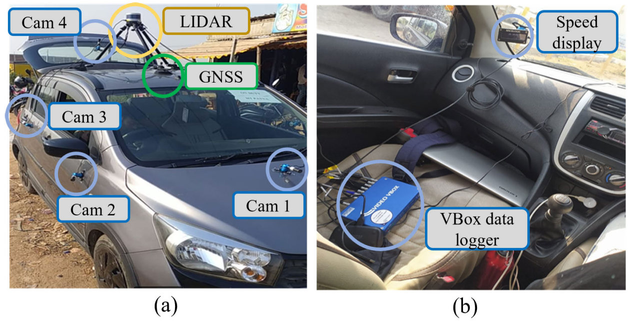


FIGURE 7. (a) Exterior of probe vehicle instrumented with VLP-16 LIDAR, GNSS engine and cameras, (b) Interior of probe vehicle indicating VBox data logger and speed display unit.

FIGURE 8. (a) Initiation of overtaking manoeuvre, (b) Completion of outgoing lane change, (c) Start of incoming lane change after passing the probe vehicle, (d) Completion of overtaking manoeuvre in the face of oncomer.

Glennon's model are compared with those from empirical data, the details of which are discussed hereafter.

A. DATA COLLECTION SITE

The data collection site has the following characteristics (Fig. 6):

- Two-lane two-way national highway (NH 922);
- A 7 to 7.5-m-wide carriageway with 1 m paved shoulders on both sides;
- Speed limit of 80 km/h on the facility;
- Straight section with negligible curvature, which can limit driver visibility;
- Moderate traffic volume (upto 600 vehicles/h) to ensure overtaking manoeuvres;
- Absence of intersections and roadside friction, which can cause interference with traffic.
- Daytime, clear weather, and dry pavement conditions.

B. INSTRUMENTED VEHICLE SETUP

Empirical data was collected on overtaking manoeuvres using unmanned aerial vehicles (UAVs) and an instrumented vehicle in prevailing heterogeneous traffic conditions. The instrumented vehicle used was a Maruti Suzuki Celerio, which was equipped with a Video VBox data logger (RLVD20P) [44] and Velodyne Puck LIDAR (VLP-16) [45]. The VBox consists of a GNSS engine that records the geo-coordinates of the vehicle at an update rate of 20 Hz with a 60 cm accuracy (95% circle of error probable) [44]. It has a set of 4 cameras, which can record at 720p at a frame rate of 25 frames per second. The cameras are installed at the bonnet, front right door, rear right door and rear windshield (see Fig. 7), to get an all-round view during the travel. This can be seen in Fig. 8. Furthermore, the inputs from GNSS and cameras were stored in an SD card installed in the data logger (Fig. 7).

Secondly, LIDAR was installed on the roof of the instrumented vehicle to perceive the roadway and traffic environment. VLP-16 has 16 channels, recording up to 0.3 million points every second. The LIDAR has a maximum range of 100 m and records with an accuracy of ± 3 cm. The height of the LIDAR was fixed with a tripod at a level for recording the surrounding traffic only (Fig. 7). The data generated from the LIDAR was stored on an onboard laptop. It should be noted that the optimal placement of VBox cameras and LIDAR was decided after conducting preliminary test runs. The test runs also assisted in mitigating certain issues and errors, which proved helpful in the actual data collection.

VBox cameras and LIDAR can only offer limited visual perception in real-life conditions (< 50 m), making it difficult to estimate the time-series spacings between the vehicles. Therefore, a pair of DJI Mavic drones were used to record the test stretch from the top-down view. These drones offered stable video footage from a height of 110 m, at a resolution of 1080p at 30 frames per second.

C. DATA COLLECTION AND EXTRACTION

The instrumented vehicle was driven in the test stretch (Fig. 9) covered by UAVs at pre-determined speeds lower than average traffic speed so that other cars could overtake the instrumented vehicle. The speed differential was maintained in the range of (10-20) km/h, as indicated in the literature [5],

FIGURE 9. Magnified view of the two-lane two-way highway from UAV footage.

[33]. Multiple runs were conducted along the test stretch while the UAV was in flight. Ultimately, the UAV helped record the trajectories of the passer, impeder and oncomer vehicles in 72 overtakes during the data collection. 23 overtakes belonged to cases where a car passed the instrumented vehicle.

During the runs, the VBox cameras record the vehicle type for the passer and the oncomer. This was intended as the vehicle type may not be evident in some instances in the UAV footage (Car vs. LCV). Moreover, all devices were time synchronised for seamless extraction of the critical manoeuvres in the overtaking process, such as encroachment into the opposite lane, completion of outgoing lane change, passing ahead, the start of return lane change and completion of overtake (Fig. 8). The LIDAR recorded the traffic environment around the instrumented vehicle as point clouds.

The trajectory data was extracted from the UAV footage using a semi-automated trajectory extraction tool (SAVETRAX v1.0 [46]). SAVETRAX is a MATLAB-based application that can extract vehicle trajectories from camera footage and is independent of camera angle, terrain type, and road geometry. After trajectory extraction, trajectories were smoothened using a recursively-ensembled low pass filter [47], [48]. Post trajectory extraction, vehicle types were validated in the trajectory data with VBox camera footage. The velocity of the passing vehicles in close range of the instrumented vehicle was corroborated with LIDAR data, and the errors were found to be within acceptable limits ($\pm 2\%$). The architecture of the instrumented vehicle for the overall data collection process is shown in Fig. 10.

D. DATA ANALYSIS

The values of parameters were adapted to simulate Glennon's model, including assuming constant speeds for the impeder and oncomer. The empirical data was filtered for the cases where a car is passing another car to ensure consistent comparison with Glennon (PSD design for cars only). The distance required to complete the overtake after reaching the critical position was obtained from the data and compared with that of Glennon. It should be noted that the oncomer was not considered, as there were several manoeuvres in the field in the absence of an oncomer. The scatter plot depicting both can be seen in Fig. 11. A student's t-test was conducted to compare the overtaking distance obtained from Glennon's model and the empirical data. The null and alternative hypotheses formulated are:

- H_o: There is no significant difference between the overtaking distance obtained from Glennon's model and empirical data.
- H_a: A significant difference exists between the overtaking distance obtained from Glennon's model and empirical data.

For a dataset of 23 overtakings, the test statistic was obtained as $t(22) = 4.04, p = 0.0002 (< 0.05)$. This suggests sufficient evidence to reject H_o, indicating a significant difference between the overtaking distance from Glennon's model (M = 53.53 m, SD = 16.19 m) and the empirical data (M = 78.19 m, SD = 23.64 m). Therefore, it is evident that Glennon's model cannot replicate the field manoeuvres precisely. This can be attributed to the driving behaviour during field overtaking manoeuvres, which may differentiate how two drivers pass under similar conditions. A driver who has experienced prolonged car-following and sporadic gaps may pass using a shorter distance than a driver travelling at the same speed in more favourable conditions. Moreover, this difference can be attributed to the lateral motion of the vehicle and vehicle dynamic response during an overtake, which Glennon neglects. This was probably due to the focus being on deriving PSD. However, it becomes essential to model the vehicle's lateral motion and dynamic response to comprehend the overtaking process, which involves two-lane changes where the vehicle is subject to lateral motion.

VI. ANALYTICAL MODEL FOR PSD

As seen in the previous sections, the PSD values obtained from Glennon's model are lower by a large margin than those obtained from IPG-CM. Moreover, the model cannot replicate the scenario in the field. This motivates the need to understand the passing manoeuvre of a vehicle on a two-lane highway at the microscopic level in the interest of safety. This section proposes an analytical model which can be tuned to obtain safe values of PSD. This could lead to more advanced analytical models for developing two-lane highway safety standards.

Yang et al. [49] proposed using a cubic polynomial trajectory for lane-change manoeuvres and deemed it the best approximation of a vehicle's lateral movement. This also agrees with the empirical data used in the previous section, where the lane change manoeuvres fit reasonably well as cubic polynomials. The use of such a trajectory for modelling vehicle motion in mixed traffic was further studied in [50] with suitable constraints on the trajectory. This trajectory model is adapted here to suit the conditions on a two-lane highway in the presence of an oncomer.

A. TRAJECTORY MODEL

The calculation of PSD using the currently proposed analytical model involves a reverse approach, where the desired final

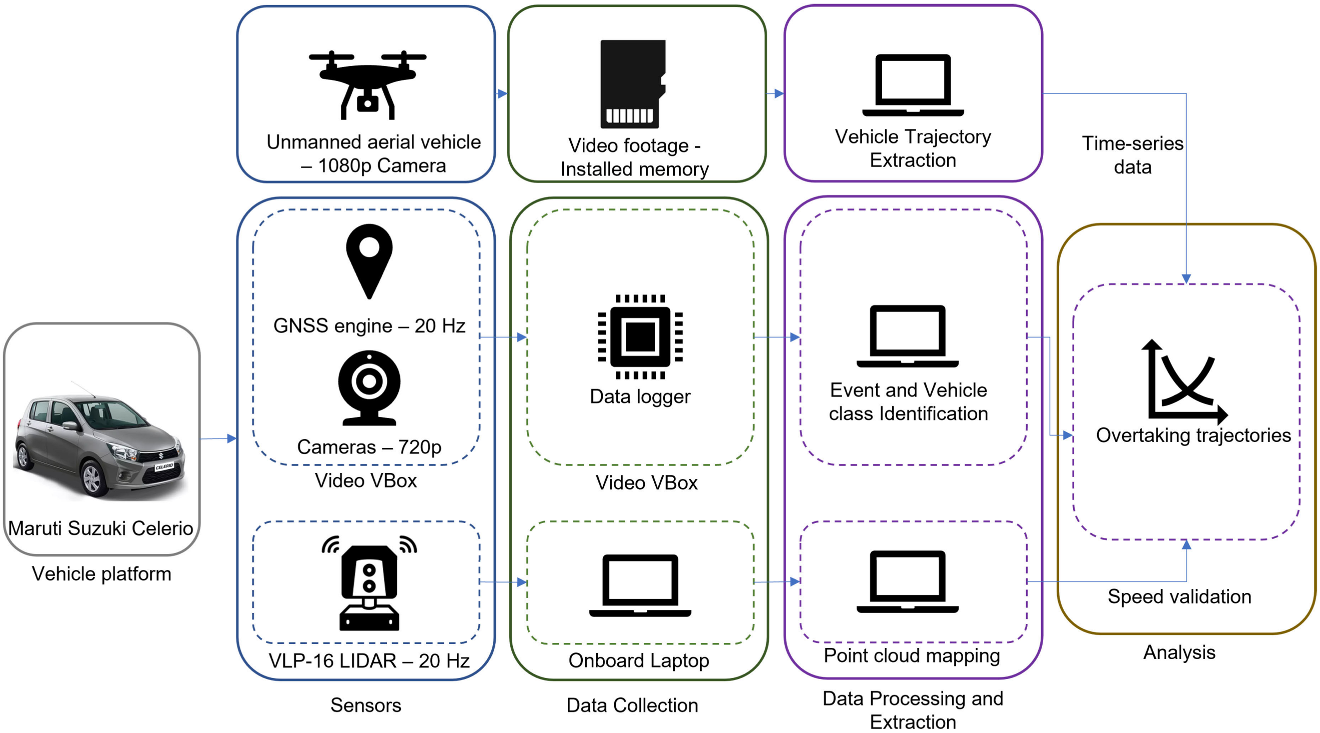


FIGURE 10. Architecture of the instrumented vehicle equipped with Video Vbox, VLP-16 LIDAR, and supplemented with UAV for empirical data collection.

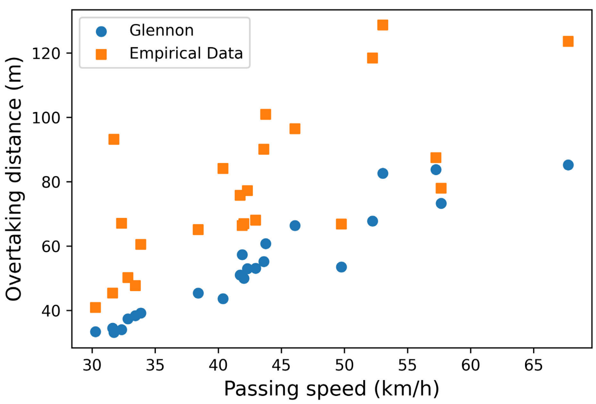


FIGURE 11. Scatter plot indicating the overtaking distance from Glennon's model and empirical data.

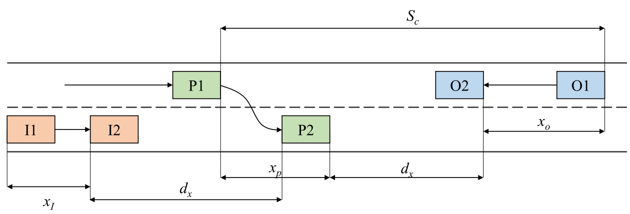


FIGURE 12. Analytical model for PSD with a cubic polynomial trajectory.

positions of the vehicles are used to estimate their feasible positions at the start of the reverse lane-change manoeuvre. According to the definition of critical PSD, the longitudinal distance between the passer and the oncoming vehicle is measured at the point beyond which completing the passing manoeuvre would not be possible. Thus, the case where the passing manoeuvre was completed from the critical position is considered here, as shown in Fig. 12.

The first step is finding x_p, which indicates the minimum longitudinal distance for completing the return lane change manoeuvre per vehicular constraints. This is based on the maximum limit on the curvature of the trajectory, K_{max}, which is taken as the minimum of the following values [50],

$$K_{speed} = \frac{\mu_{lat} g}{v^2}, \tag{4}$$

$$K_{steer} = \frac{\delta_{max}}{l + k_u \frac{v^2}{g}}, \tag{5}$$

$$K_{comf} = \frac{a_{comf}}{v^2}. \tag{6}$$

Here, K_{speed} is the maximum limit on the curvature of the trajectory due to lateral traction, K_{steer} is the limit due to the maximum steering angle of the wheels, and K_{comf} is the limit based on the maximum comfortable lateral acceleration. It is expected that K_{comf} would generally be the most conservative value, but the others are included to account for all possible scenarios. The lateral traction depends on the lateral friction coefficient, μ_{lat}. The other variables are the maximum vehicle steering angle δ_{max}, the speed of the passer v, the distance between the front and rear axles l, and the comfortable lateral acceleration maintained by the driver a_{comf}. The lateral acceleration is a configurable parameter that varies based on the vehicle's speed as deemed safe by the driver. The understeer gradient of the vehicle, k_u, in equation (5) is used to obtain a relationship between the curvature of the turn and the steering angle required for the turn and is given as

$$k_u = \frac{m_p g(bC_r - aC_f)}{2lC_f C_r}, \tag{7}$$

where, m_p is the mass of the passing vehicle, C_f and C_r are the cornering stiffness of the front and rear tire, respectively, a and b are the distance of the centre of gravity (CoG) from the front and rear axle respectively, and g represents acceleration due to gravity. The values of these parameters are shown in Table 3.

It is assumed that the trajectory traced by the vehicle during the lane change can be approximated using a cubic polynomial trajectory. The equation of the trajectory is given by [49]

$$y = c_1 x + c_2 x^2 + c_3 x^3, \tag{8}$$

where,

$$\begin{aligned} c_1 &= \tan(\theta_i), \\ c_2 &= \frac{3\,y_p - 2\,x_p\,\tan(\theta_i)}{x_p^2}, \\ c_3 &= \frac{x_p\,\tan(\theta_i) - 2\,y_p}{x_p^3}. \end{aligned} \tag{9}$$

Here, θ_i is the initial heading angle, which is the slope of the trajectory, $(x_p,\ y_p)$ is the final desired waypoint, and the heading angle at the desired waypoint is assumed to be zero [51].

As shown by [49] and [50], the value of x_p is obtained from the maximum curvature of the cubic polynomial trajectory, K_{max}, as

$$K_{max} = \left| \frac{2x_p \tan(\theta_i) - 6\,y_p}{(x_p)^2} \right|. \tag{10}$$

Assuming the initial heading angle of the vehicle, θ_i, to be zero,

$$K_{max} = \left| \frac{-6\,y_p}{(x_p)^2} \right|, \tag{11}$$

where y_p is the distance moved laterally, equal to the lane width of 3.5 m. The safe gap maintained by the driver, d_x is calculated by assuming the model as

$$d_x = c_t(v + v_o) + \beta L_i, \tag{12}$$

where, β is a calibrated parameter that denotes the weight given to the margin in vehicle lengths. c_t is the clearance time taken as 0.75 s. This value has been set higher than what is reported in the literature for moderate-high traffic volumes (0.6 s, [52]) to ensure a higher level of safety. At the same time, c_t is not as high as Glennon (1 s) to reflect advancements in braking systems and provide a realistic estimate. L_i is the length of the impeding vehicle, the same as that of the oncoming vehicle. After tuning, β was set as 1 to provide a minimum safety margin of one-vehicle length.

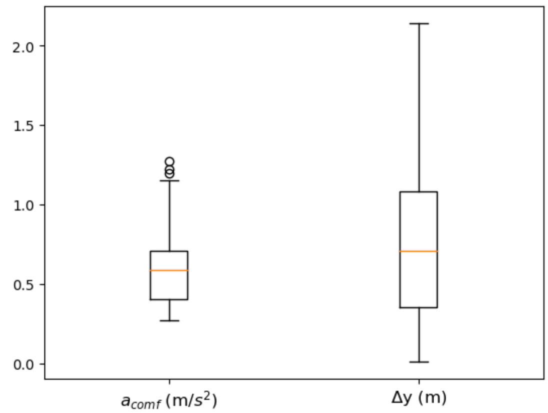


FIGURE 13. Box plots indicating the distribution of comfortable acceleration and change in lateral position during lane change.

Further, the longitudinal distance travelled by the oncoming vehicle is estimated by using the time required for the passer to complete its lateral manoeuvre, given as

$$x_o = \frac{v_o L_{total}}{v}, \tag{13}$$

where v_o is the speed of the oncoming vehicle, taken to be the same as v here. Hence, $x_o = L_{total}$ in this case. The length of the trajectory, L_{total}, is calculated by integrating segments d_s of the trajectory as [49] and [50]

$$L_{total} = \int_0^{x_p} d_s \mathrm{d}x, \tag{14}$$

where

$$d_s = \sqrt{1 + \left(x\frac{6y_p}{x_p^2} - x^2\frac{6y_p}{x_p^3} \right)^2}. \tag{15}$$

This gives the critical PSD as

$$S_c = x_p + d_x + L_{total}. \tag{16}$$

More details of modelling using this framework can be found in [49] and [50].

B. COMPARISON WITH IPG-CM

The resulting PSD values from this preliminary analytical model are shown in Table 8. With these considerations, the difference in the PSD values with IPG-CM reduces to as low as 3.4%, with the highest difference being 4.7%. The primary reason is the consideration of proper safe gaps, which can be calibrated as per driving behaviour. Typical models consider a fixed headway maintained when overtaking, but the consideration of reaction time incorporates the constraints of the driver and vehicle. This consideration forms the term d_x, as seen in (12). Further, changing the lane requires some longitudinal distance based on the vehicle's capabilities, which is not accounted for in conventional PSD models. It can form a substantial part of the PSD, which is the term x_p in (16). This parameter is affected by the consideration of the

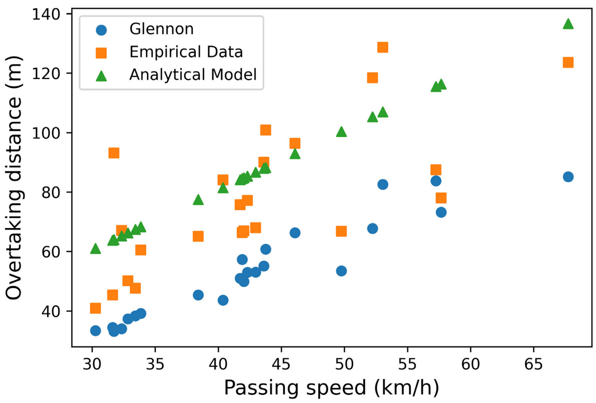


FIGURE 14. Scatter plot comparing overtaking distance from Glennon's model, empirical data, and analytical model.

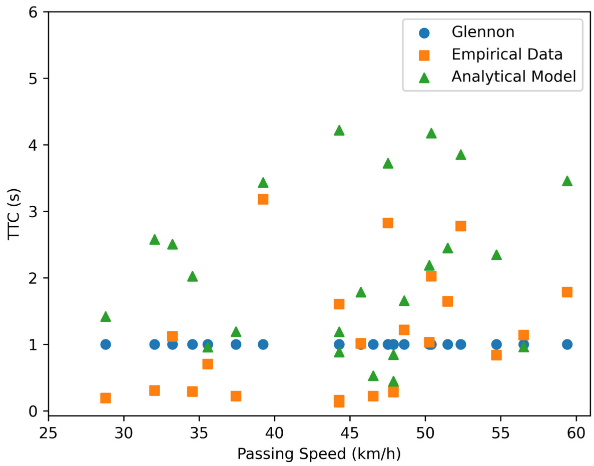


FIGURE 15. Comparison of TTC from Glennon's model, empirical data, and analytical model.

dynamic parameters of the vehicle, which are encapsulated in the curvature of the trajectory, K_{max}, as seen in (4) to (11). While IPG-CM has a higher-order vehicle model considering all vehicle dynamic parameters, the analytical model offers a few simple, configurable parameters to obtain the PSD. At the same time, considering the actual trajectory of the vehicle for passing ensures that the constraints on the manoeuvres are maintained, which leads to reasonably close values.

C. COMPARISON WITH EMPIRICAL DATA

As discussed in Section V, Glennon's model could not replicate the overtaking scenarios in the field. Consequently, the overtaking distance required by cars to overtake was lower by up to 30%, as per Glennon, when compared to actual distances from the field. The mean absolute error (MAE) and mean absolute percentage error (MAPE) between Glennon's and field values were 24.67 m and 30%, respectively. Glennon was found to underestimate the overtaking distances at all speeds, which indicates collision risks during overtaking. This agrees with previous studies' results [23], [33], which compared design PSD values with empirical data. This motivated the development of an analytical overtaking model incorporating vehicle dynamic response. The input parameters were calibrated using field data to compare the empirical data and the analytical model consistently. This included considering the actual dimensions and weight of the vehicle obtained from the field. Moreover, the values of comfortable lateral acceleration (a_{comf}) were calculated using field manoeuvres. The 95th percentile was selected as 1.2 m/s^2 to ensure the inclusion of most drivers in design. Moreover, the change in lateral position was used as 1.2 m (95th percentile), as not all drivers attempt the lane change manoeuvre using full lane width. The distribution of the parameters calibrated using field data can be seen in Fig. 13. The overtaking distance from Glennon, empirical data, and the analytical model are shown in Fig. 14. The MAE and MAPE between the analytical model and field values were 15.88 m and 22.76%, which is lower than Glennon (24.67 m, 30%). The overtaking distance obtained from the analytical model is closer than required in the field. Using the ANOVA test to investigate their differences, a statistical comparison was made between the PSD values obtained from the three groups- Glennon's model, empirical data and analytical model. The following null and alternative hypotheses were formulated:

- H_o: No significant difference exists among the means of the three groups - Glennon's model, empirical data and analytical model.
- H_a: Significant difference exists among the means of the three groups - Glennon's model, empirical data and analytical model.

The test statistic was obtained as $F = 16.26$; $p = 1.8075e-06$ (< 0.05). This suggests evidence to reject H_o, indicating a significant difference between the overtaking distance from Glennon's model, empirical data and analytical model. Also, the student's t-test indicates no significant difference between the empirical data (M = 78.2 m, SD = 24.17 m) and the analytical model (M = 86.5 m, SD = 19.8 m) $(t(22) = 1.28, p = 0.206(> 0.05))$. This is in contrast to the comparison between Glennon's model and the empirical data, discussed in Section V. Furthermore, a post-hoc test was conducted to find which pairs differ significantly among the three - (a) Glennon's model, (b) Empirical data, and (c) Analytical model. Tukey's HSD test [53] was chosen to compare the means of the differences in the three groups. The test statistics were calculated as: (1) $Q_{ab} = 5.61$, $p = 0.001$ (< 0.01); (2) $Q_{ac} = 8.48$, $p = 0.001$ (< 0.01); (3) $Q_{bc} = 2.87$, $p = 0.11$ (> 0.01). This suggests that a significant difference exists between Glennon's model and empirical data. Moreover, Glennon's model differs significantly from the analytical model. However, the difference between the empirical data and the analytical model is not significant. Therefore, the analytical model outperforms Glennon's model and provides closer estimates of overtaking distance than the field. This signifies the importance of analysing the microscopic motion of a vehicle, considering vehicular constraints and driver behaviour. However, some drivers overtake using lesser distances than what is obtained

TABLE 8. PSD comparison for analytical model with IPG-CM.

Speed of Passer (v, km/h)	Speed differential (m, km/h)	Lateral acceleration (a_{comf}, m/s^2)	Critical PSD from Glennon's Model (S_c, m)	Critical PSD from IPG-CM (S_c, m)	Critical PSD from Analytical Model (S_c, m)	Difference in Analytical Model and IPG-CM PSD (%)
40	20.14	0.5	121.1	159.0	165.6	4.2
50	19.14	0.5	153.8	197.3	205.7	4.3
60	18.14	0.5	185.4	258.0	245.9	4.7
70	17.14	0.5	216.1	296.6	286.0	3.6
80	16.14	0.35	246.0	396.0	382.4	3.4
90	15.14	0.2	275.1	531.6	554.7	4.3
100	14.14	0.2	303.4	588.2	615.8	4.7

from the analytical model, which indicates aggressive driving or accepting shorter gaps, possibly motivated by situations such as prolonged following.

D. SAFETY ANALYSIS

This subsection evaluates the analytical model for its safety performance, considering head-on collision risks. For this, we utilise minimum time to collision (TTC$_{min}$) as an indicator to compare the analytical model with empirical data and Glennon's model. TTC$_{min}$ has been employed by researchers frequently to quantify collision risks [27], [52], [54], [55]. It indicates the remaining time between the passing and opposing vehicle at the end of the manoeuvre. Mathematically, it is the ratio of the clearance distance between the vehicles to their relative speed at the end of the manoeuvre. The equation for TTC$_{min}$ can be given as [52]:

$$\mathrm{TTC}_{min} = \frac{x_o - x_p - l}{v_o - v_p}, \tag{17}$$

where x_o and x_p are the positions of the centre of oncomer and passer at the end of the pass, respectively, l indicates the length of the vehicle, v_o and v_p are the speeds of the oncomer and passer at the end of the pass. The minimum TTC for the three cases can be defined as:

- Glennon's model: Glennon assumes a clearance of $2v_p$ at the end of the overtake, where v_p is the passer's speed (equal to v_o). It should be noted that Glennon ignores the length term while computing clearance. Consequently, TTC$_{min}$ can be found as 1 s. Therefore, Glennon assumes a constant TTC$_{min}$ of 1 s, irrespective of speeds.
- Empirical data: TTC$_{min}$ was computed by taking the ratio of the clearance between the passer and the oncomer at the end of overtake when the passer has completely encroached into his lane, to the relative speed $(v_o + v_p)$.
- Analytical model: The clearance at the end of the manoeuvre was obtained using the difference between the longitudinal gap at the critical position and the distance required for a lane change (x_p in Fig. 12). The ratio of the obtained clearance with the relative speed $(v_o + v_p)$ will yield TTC$_{min}$. The comparison of the TTC values can be seen in Fig. 15

The mean TTC$_{min}$ for points in Fig. 15 for Glennon's model, empirical data, and the analytical model is given as 1 s, 1.09 s, and 2.12 s, indicating the mean TTC$_{min}$ provided by the analytical model is higher than Glennon. Moreover, the values obtained using the analytical model agree with those recommended in the AASHTO safety manual (2 s, [56]). To compare the TTC values obtained from the model with the empirical data, a one-tailed student's t-test was conducted. The following null and alternative hypotheses were formulated:

- H_o: No significant difference exists among the means of the TTC$_{min}$ between the empirical data and the analytical model.
- H_a: TTC$_{min}$ provided by the analytical model is greater than the existent TTC$_{min}$ in field.

The test statistic was obtained as: $t_{stat} = 3.26, p = 0.001(< 0.05)$. Thus, sufficient evidence exists to reject H_o, indicating that TTC$_{min}$ provided by the analytical model is greater than the existent TTC$_{min}$ in the field. Hence, the analytical model outperforms Glennon by providing a higher TTC when compared to the actual TTC used by the drivers in the field. This will increase safety margins, enhancing vehicle safety during overtaking manoeuvres. To address this, Eq. 12, which is in line with TTC$_{min}$ can be applied to calibrate for different overtaking scenarios.

VII. CONCLUSION

This paper examined existing PSD standards and compared them with realistic values. A seminal PSD model, Glennon's model, was compared with values from IPG-CM. Furthermore, Glennon's model was evaluated for varying roadway parameters, including longitudinal gradient and tire-road friction. The model was then benchmarked using empirical data to analyse its performance in field conditions. Finally, an analytical overtaking model is proposed, and its performance is tested against empirical data and Glennon's model. The insights and implications from our study have been summarised:

- The deviations between PSD obtained from IPG-CM and Glennon were as high as 94% for specific road conditions. This indicates the inadequacy of PSD standards based on Glennon's model and implies the need for an improved model. This agrees with the conclusions of previous studies [23], [33].
- PSD was found to increase marginally with an increase in longitudinal gradient. In contrast, PSD increased with

a decrease in tire-road friction by 12% at speeds of 70 km/h. Most models did not account for road parameter changes, leading to the values deviating from realistic ones. Therefore, the fluctuation of road parameters from standard conditions poses a safety risk within the context of PSD.

- Glennon's model was benchmarked against empirical data from a two-lane highway. The comparison indicated a significant difference between the overtaking distance, indicating the inability of Glennon's model to replicate the overtaking manoeuvres in the field.
- Owing to the limitations in Glennon's model, an analytical overtaking model was proposed to understand the overtaking process better. Furthermore, the PSD values from the analytical model were compared with simulations, and the obtained deviation was less than 5%.
- The analytical model performed better than Glennon's model when tested against empirical data. The overtaking distances obtained from the analytical model being closer to the empirical data show the importance of analysing the microscopic motion of a vehicle, which also leads to the consideration of vehicular constraints and driver behaviour.
- The analytical model outperforms Glennon's model by providing a higher TTC_{min} for field overtakes. Moreover, the provided TTC_{min} agrees with the guidelines (2 s). Adapting guidelines considering overtaking scenarios in the field may provide a balance between safety and efficiency.

To conclude, this study aimed to develop an analytical overtaking model that can provide safe PSD estimates closer to field values. An analytical model such as this takes the best of mathematical and field data-based models by applying physical vehicle constraints and allowing for specific configurable parameters. Therefore, the model incorporated vehicle dynamics and driver behaviour to simulate overtaking manoeuvres more accurately. Furthermore, the developed model was tested against a benchmark model using real-world data. The results indicated significant improvements in feasibility (overtaking distance) and safety (TTC_{min}). By achieving superior performance over established models, the proposed analytical model demonstrates that the objectives have been met. The findings from this study make several contributions to the research field:

1) Research: The validity of Glennon's Model (state-of-the-practice model) was evaluated using simulation and empirical data. By comparing the model's estimates of overtaking distance, we provided insights into the model's performance, indicating the need for improvement. Towards this, we propose an overtaking model that accurately replicates the overtaking behaviour. Furthermore, the proposed model is flexible to account for vehicle and roadway parameters, making it more adaptable to various situations. Therefore, researchers can employ the proposed model to obtain accurate PSD estimates and predict overtaking behaviour for connected and autonomous vehicle applications.
2) Safer geometric design: The proposed model can be applied to gather insights into overtaking manoeuvres. Road designers can use the model to compute a safe and optimised PSD for various scenarios. The calculated PSD can be provided in sections with frequent unsafe overtakes by providing additional passing zones and improving visibility. This will enhance road safety.
3) Improved traffic operations: Traffic planners can use the proposed model in congested sections to optimise the traffic flow. This will improve the average travel speed and level of service on the roadway facility.
4) Policymaking: The proposed model can be incorporated in a traffic micro-simulation to study the effect of a planned decision on the overtaking manoeuvres and its impact on the safety and operations of the roadway facility. Moreover, this will help mitigate potential risks that may occur with changes in roadway design and traffic rules.
5) Application in ADAS systems: Sensors mounted on a vehicle can analyse the traffic conditions, roadway geometry and environmental conditions. By providing this data to a controller integrated with the proposed model, overtaking alerts can be issued to drivers. This will assist the drivers in making safer overtaking decisions considering a wide range of factors.

This study has merits which differentiate it from previous studies. Firstly, a vehicle-dynamics-based simulation was employed in this study to enable a controlled environment for testing various scenarios. The effect of multiple variables (such as gradient and tire-road friction), which are cumbersome to evaluate in the field, was now possible using the simulation. Secondly, this study used a novel data collection methodology where an instrumented vehicle was supplemented with a UAV to collect the field data. The sensors installed in the instrumented vehicle offer limited detection only in the vehicle's vicinity. The use of a UAV enabled us to overcome this limitation. Moreover, it assisted in the collection of overtaking trajectories involving other vehicles in the traffic stream. Hence, integrating the data from multiple sources (instrumented vehicle and UAV) helped enhance the reliability of the recorded data. Finally, empirical data used for benchmarking was a definite improvement over previous studies, which did not validate their results using field data. Furthermore, empirical data enabled us to make a three-way comparison between the existing model and the proposed model, which also helped establish the performance of the proposed model.

Notwithstanding the study's strengths, it is essential to recognise its limitations. Firstly, this study used trajectory data collected from a two-lane highway in India to validate the proposed model. This may impact the model's generalizability to varying traffic conditions and driving behaviour. Secondly, assumptions such as uniform road conditions and rational driver behaviour may restrict the model from capturing the complexity of field scenarios and could be relaxed for improved performance.

The future scope lies in the further tuning and adaptation of the model to different road scenarios and driving behaviours by appropriately choosing the configurable parameters. This will ensure the model's performance in various conditions. The impact of environmental factors on overtaking behaviour, such as visibility and weather conditions, can be another avenue to explore. The model can be applied to ascertain changes in roadway design, such as speed limits, signage, and visibility. The effectiveness of these policy interventions on the safety and operations of the two-lane roads needs to be studied. The model can be integrated with ADAS systems to issue alerts to the drivers. Calibrating such systems to work precisely with a range of vehicles and drivers' characteristics can be explored. Further, the model can also be adapted to consider the longitudinal capabilities of other vehicle classes, such as trucks.

REFERENCES

[1] *Road Accidents in India—2018*, Transp. Res. Wing, Ministry Road Transp. Highways, Government India, New Delhi, India, 2019.

[2] *Road Accidents in India—2020*, Ministry Road Transp. Highways, Government India, New Delhi, India, 2021.

[3] Insurance Information Institute. (2020). *Facts + Statistics: Highway Safety*. Accessed: Mar. 14, 2023. [Online]. Available: https://www.iii.org/fact-statistic/facts-statistics-highway-safety

[4] H. Farah, ''When do drivers abort an overtaking maneuver on two-lane rural roads?'' *Transp. Res. Rec.*, vol. 2602, no. 1, pp. 16–25, 2016.

[5] A. Maji, B. Bhadrecha, and P. Bhattacharya, ''Overtaking distance models for passenger cars in two-lane undivided rural highways,'' *J. Inst. Eng. India A*, vol. 102, no. 3, pp. 773–782, Sep. 2021.

[6] *Basic Road Statistics of India*, MoRTH, Ministry Road Transp. Highways, Chennai, India, 2017.

[7] D. Harwood, D. Gilmore, and K. Richard, *Passing Sight Distance Criteria* (National Cooperative Highway Research Program). Transp. Res. Board, Washington, DC, USA, 2008.

[8] G. W. Van Valkenburg and H. L. Michael, ''Criteria for no-passing zones,'' HRB, Nat. Res. Council, Ottawa, ON, Canada, Tech. Rep. Highway Res. Rec. 377, 1971, pp. 1–19.

[9] G. D. Weaver and J. Glennon, ''Design and striping for safe passing operations,'' HRB, Nat. Res. Council, Ottawa, ON, Canada, Tech. Rep. Highway Res. Rec. 388, 1972, pp. 36–39.

[10] D. W. Harwood and J. Glennon, ''Framework for design and operation of passing zones on two-lane highways,'' TRB, Nat. Res. Council, Ottawa, ON, Canada, Tech. Rep. Transp. Res. Rec. 601, 1976, pp. 45–50.

[11] J. C. Glennon, ''New and improved model of passing sight distance on two-lane highways,'' *Transp. Res. Rec.*, vol. 1195, pp. 132–137, 1988.

[12] *AASHTO Green Book (GDHS-7)—A Policy on Geometric Design of Highways and Streets*, 7th ed., Amer. Assoc. State Highway Transp. Off. (AASHTO), Washington, DC, USA, 2018.

[13] J. C. Mertens, J. Hauenstein, F. Diermeyer, L. Jahn, and S. Kraus, ''Cooperative truck overtaking on freeways,'' in *Proc. 15th Int. Conf. Ecol. Vehicles Renew. Energies (EVER)*, Sep. 2020, pp. 1–15.

[14] A. Takemoto, K. Munehiro, N. Takahashi, S. Kasai, S. Yamamoto, and K. Tsutsumi, ''Construction of passing-maneuver model on two-lane highway with consideration of road surface and visibility conditions,'' *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2258, no. 1, pp. 110–118, Jan. 2011.

[15] *AASHO Policy on Geometric Design of Highways and Streets*, Amer. Assoc. State Highway Off., Washington, DC, USA, 1954.

[16] S. Bassan, ''Review and design policy of sight distance types for the interurban highway system,'' *Proc. Inst. Civil Eng., Transp.*, vol. 172, no. 5, pp. 274–288, Oct. 2019.

[17] E. B. Liebermann, ''Model for calculating safe passing sight distance on two-lane rural roads,'' TRB, Nat. Res. Council, Ottawa, ON, Canada, Tech. Rep. Transp. Res. Rec. 869, 1982, pp. 70–76.

[18] M. Saito, ''Evaluation of the adequacy of the MUTCD minimum passing sight distance requirement for aborting the passing maneuver,'' *ITE J.*, vol. 54, no. 1, pp. 18–22, 1984.

[19] D. W. Harwood and J. C. Glennon, ''Passing sight distance design for passenger cars and trucks,'' *Transp. Res. Rec.*, vol. 1208, pp. 59–69, 1989.

[20] L. R. Rilett, B. G. Hutchinson, and M. Whitney, ''Mechanics of the passing maneuver and the impact of large trucks,'' *Transp. Res. A, Gen.*, vol. 24, no. 2, pp. 121–128, Mar. 1990.

[21] Y. Hassan, S. M. Easa, and A. O. A. E. Halim, ''Passing sight distance on two-lane highways: Review and revision,'' *Transp. Res. A, Policy Pract.*, vol. 30, no. 6, pp. 453–469, 1996.

[22] M. T. Haq, A. Farid, and K. Ksaibati, ''Estimating passing sight distances for overtaking truck platoons—Calibration and validation using VISSIM,'' *Int. J. Transp. Sci. Technol.*, vol. 11, no. 2, pp. 255–267, Jun. 2022.

[23] A. Polus, M. Livneh, and B. Frischer, ''Evaluation of the passing process on two-lane rural highways,'' *Transp. Res. Rec., J. Transp. Res. Board*, vol. 1701, no. 1, pp. 53–60, Jan. 2000.

[24] C. Llorca and A. García, ''Evaluation of passing process on two-lane rural highways in Spain with new methodology based on video data,'' *Transp. Res. Rec., J. Transp. Res. Board*, vol. 2262, no. 1, pp. 42–51, Jan. 2011.

[25] K. M. Arun Sagar, P. N. Salini, R. Ashalatha, and B. S. Mathew, ''Prediction of passing probability and risk evaluation along undivided road under heterogeneous traffic,'' *Int. J. Injury Control Saf. Promotion*, vol. 30, no. 1, pp. 132–142, Jan. 2023.

[26] M. Gao, Y. Zhao, Y. Shen, X. Yu, S. Gou, and Q. Bao, ''Which factors are most relevant to drivers' overtaking choices at two-lane highways: A comparative analysis between questionnaire surveys and driving simulation,'' *Transp. Res. F, Traffic Psychol. Behav.*, vol. 95, pp. 202–214, May 2023.

[27] V. Branzi, M. Meocci, L. Domenichini, and M. Calcinai, ''A combined simulation approach to evaluate overtaking behaviour on two-lane two-way rural roads,'' *J. Adv. Transp.*, vol. 2021, pp. 1–18, Aug. 2021.

[28] S. Mavromatis, ''Passing distance examination over single and platooned heavy military vehicles,'' in *Proc. 10th Int. Congr. Transp. Res.*, 2021, pp. 6–12.

[29] S. M. S. Mahmud, L. Ferreira, M. S. Hoque, and A. Tavassoli, ''Overtaking risk modeling in two-lane two-way highway with heterogeneous traffic environment of a low-income country using naturalistic driving dataset,'' *J. Saf. Res.*, vol. 80, pp. 380–390, Feb. 2022.

[30] H. Farah, ''Modeling drivers' passing duration and distance in a virtual environment,'' *IATSS Res.*, vol. 37, no. 1, pp. 61–67, Jul. 2013.

[31] A. Vetters and T. Jaehrig, ''Verification of the existing model for passing sight distance on single two-lane rural carriageways,'' in *Proc. 6th IEEE Int. Conf. Cogn. Infocommun. (CogInfoCom)*, Oct. 2015, pp. 557–561.

[32] A. C. Figueira and A. P. C. Larocca, ''Analysis of the factors influencing overtaking in two-lane highways: A driving simulator study,'' *Transp. Res. F, Traffic Psychol. Behav.*, vol. 69, pp. 38–48, Feb. 2020.

[33] T. Choudhari, A. Budhkar, and A. Maji, ''Modeling overtaking distance and time along two-lane undivided rural highways in mixed traffic condition,'' *Transp. Lett.*, vol. 14, no. 2, pp. 75–83, 2020.

[34] G. Asaithambi and G. Shravani, ''Overtaking behaviour of vehicles on undivided roads in non-lane based mixed traffic conditions,'' *J. Traffic Transp. Eng., English Ed.*, vol. 4, no. 3, pp. 252–261, Jun. 2017.

[35] *A Policy on Geometric Design of Highways and Streets*, Amer. Assoc. State Highway Transp. Off. (AASHTO), Washington, DC, USA, 2018.

[36] P. S. Bokare and A. K. Maurya, ''Acceleration-deceleration behaviour of various vehicle types,'' *Transp. Res. Proc.*, vol. 25, pp. 4733–4749, Jan. 2017.

[37] C. M. Kang, S.-H. Lee, and C. C. Chung, ''Comparative evaluation of dynamic and kinematic vehicle models,'' in *Proc. 53rd IEEE Conf. Decis. Control*, Dec. 2014, pp. 648–653.

[38] C. M. Kang, S.-H. Lee, and C. C. Chung, ''Vehicle lateral motion estimation with its dynamic and kinematic models based interacting multiple model filter,'' in *Proc. IEEE 55th Conf. Decis. Control (CDC)*, Dec. 2016, pp. 2449–2454.

[39] Z. F. Magosi, C. Wellershaus, V. R. Tihanyi, P. Luley, and A. Eichberger, ''Evaluation methodology for physical radar perception sensor models based on on-road measurements for the testing and validation of automated driving,'' *Energies*, vol. 15, no. 7, p. 2545, Mar. 2022.

[40] J. G. Kale, A. Subramaniam, M. L. Karle, and U. S. Karle, "Simulation based design and development of test track for adas functions validation and verification with respect to Indian scenario," SAE Tech. Paper 2019-26-0100, 2019.

[41] D. Nalic, A. Eichberger, G. Hanzl, M. Fellendorf, and B. Rogic, "Development of a co-simulation framework for systematic generation of scenarios for testing and validation of automated driving systems," in *Proc. IEEE Intell. Transp. Syst. Conf. (ITSC)*, Oct. 2019, pp. 1895–1901.

[42] *IPGDriver User Manual Version 8.1*, IPG Automot., Karlsruhe, Germany, 2019.

[43] *A Policy on Geometric Design of Highways and Streets*, Amer. Assoc. State Highway Transp. Off., Washington, DC, USA, 2011.

[44] VBox Automotive. (2023). *VBOX Video Data Loggers*. Accessed: May 21, 2023. [Online]. Available: https://www.vboxautomotive.co.uk/index.php/en/products/data-loggers/video-data-loggers

[45] Velodyne. (2023). *Puck LiDAR Sensor, High-Value Surround LiDAR*. Accessed: Jun. 21, 2023. [Online]. Available: https://velodynelidar.com/products/puck/

[46] S. Venthuruthiyil and M. Chunchu, "SAVETRAX: A semi-automated image processing based vehicle trajectory extractor," in *Proc. 99th Annu. Meeting Transp. Res. Board*, 2020.

[47] S. P. Venthuruthiyil and M. Chunchu, "Vehicle path reconstruction using recursively ensembled low-pass filter (RELP) and adaptive tri-cubic kernel smoother," *Transp. Res. C, Emerg. Technol.*, vol. 120, Nov. 2020, Art. no. 102847.

[48] S. P. Venthuruthiyil and M. Chunchu, "Trajectory reconstruction using locally weighted regression: A new methodology to identify the optimum window size and polynomial order," *Transportmetrica A, Transp. Sci.*, vol. 14, no. 10, pp. 881–900, Nov. 2018.

[49] D. Yang, S. Zheng, C. Wen, P. J. Jin, and B. Ran, "A dynamic lane-changing trajectory planning model for automated vehicles," *Transp. Res. C, Emerg. Technol.*, vol. 95, pp. 228–247, Oct. 2018.

[50] P. Deshpande, R. Amrutsamanvar, and S. C. Subramanian, "Vehicle path generation and tracking in mixed road traffic," *IFAC-PapersOnLine*, vol. 53, no. 1, pp. 524–529, 2020.

[51] P. Deshpande, K. Devika, S. C. Subramanian, and L. D. Vanajakshi, "Robust steering control for trajectory following in road traffic environments," *Proc. Inst. Mech. Eng. I, J. Syst. Control Eng.*, vol. 236, no. 1, pp. 153–168, Jan. 2022.

[52] F. Bella, "How traffic conditions affect driver behavior in passing maneuver," in *Advances in Transportation Studies*. Rome, Italy, 2011.

[53] H. Abdi and L. J. Williams, "Tukey's honestly significant difference (HSD) test," *Encyclopedia Res. Design*, vol. 3, no. 1, pp. 1–5, 2010.

[54] H. Farah, S. Bekhor, and A. Polus, "Risk evaluation by modeling of passing behavior on two-lane rural highways," *Accident Anal. Prevention*, vol. 41, no. 4, pp. 887–894, Jul. 2009.

[55] H. Farah and C. L. Azevedo, "Safety analysis of passing maneuvers using extreme value theory," *IATSS Res.*, vol. 41, no. 1, pp. 12–21, Apr. 2017.

[56] *Highway Safety Manual*, 1st ed., Amer. Assoc. State Highway Transp. Off., Washington, DC, USA, 2010.

ABHISHEK RAJ received the B.Tech. degree from the National Institute of Technology at Tiruchirappalli, India, in 2019. He is currently pursuing the Ph.D. degree with the Department of Civil Engineering, Indian Institute of Technology at Madras, Chennai, India.

PARTH DESHPANDE (Graduate Student Member, IEEE) received the B.Tech. and M.Tech. degrees from the Indian Institute of Technology at Madras, Chennai, India. He is currently pursuing the Ph.D. degree with the Department of Engineering, University of Cambridge, U.K., with a focus on sustainable road freight.

BHARGAVA RAMA CHILUKURI received the Ph.D. degree in civil and environmental engineering from the Georgia Institute of Technology, Atlanta, GA, USA. He has several years of professional experience as a traffic engineer in multiple companies in the USA. He is currently an Associate Professor with the Department of Civil Engineering, Indian Institute of Technology at Madras. His current research interests include the traffic flow theory of homogenous and heterogeneous traffic, traffic operations, and networks.

SHANKAR C. SUBRAMANIAN (Senior Member, IEEE) received the Ph.D. degree from Texas A&M University, USA. He is currently a Professor and a V. Ramamurti Faculty Fellow with the Department of Engineering Design, Indian Institute of Technology at Madras, Chennai, India. His current research interests include dynamics and control with applications to automotive and transportation systems.