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An ANN-based framework for estimating inconsistency in lateral placement of heterogeneous traffic

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ABSTRACT

The lateral placement is the transverse position of a moving vehicle across the carriageway width. Studies on lateral placement have gained importance over time specifically for two reasons; (1) lateral placement data has become a crucial input in most of the traffic flow simulation models, and (2) detection of wheel positions helps in determining the riding quality and the distressed portions on a pavement surface. In the case of heterogeneous traffic flow and loosely enforced lane discipline, the estimation of lateral placement of vehicles deals with additional complexity. In such cases, vehicles take any lateral position left empty by other surrounding vehicles while moving in a mixed traffic stream. This results in an inconsistent lateral trajectory of vehicles. Further, this inconsistency is primarily governed by the subject vehicle type and other prevailing factors of the traffic stream. On this background, the present study forwards a Neural Network-based approach to quantify the inconsistency associated with the lateral placements chosen by different vehicle categories in a mixed traffic situation. In addition, a sensitivity analysis revealed how the inconsistency in lateral placement varies suggestively with the change in traffic and road geometric factors.

1. Introduction

A typical urban road in a developing country accommodates a wide variety of vehicles with loosely enforced lane discipline. In a mixed traffic situation, vehicles are flexible enough to acquire any lateral gap across the carriageway width left empty by other adjacent vehicles. Vehicles belong to diverse categories having different physical dimensions and maneuverabilities. As a subsequence, small-sized and highly-maneuverable vehicles like motorized two-wheelers get frequent opportunities to squeeze through any available transverse gap and move in an untidy manner. On the other hand, heavy vehicles like trucks and buses, get fewer opportunities subject to their larger size and low maneuverability. Due to this variation, a substantial inconsistency in lateral placement is generally observed on urban roads carrying mixed traffic. Lateral placement (LP) represents the transverse position of a vehicle across the carriageway width [1]. Information regarding the lateral placement of vehicles is a prerequisite for traffic simulations [2,3], traffic flow modeling [4–7], identification of distressed portions on a pavement [8] and various other applications [9]. Owing to these utilities, the estimation of lateral placement of vehicles has been given major emphasis recently and the lateral placement-related research is gaining popularity with time. Previous studies [10] showed that the distribution of lateral placement of vehicles across the carriageway width in a mixed traffic stream can be either unimodal or bimodal but, there is an inverse relationship between the lateral placement and the speed of the subject vehicle [11]. On the other hand, Balaji et al. [12]

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developed a polynomial model in the context of an undivided urban road and observed that the lateral placement of a vehicle shifts more towards the center of the road with the increase in vehicular speed. Similarly, in the case of divided roads, the fast-moving vehicles prefer to move on the median lane as compared to the shoulder lane [11]. In order to predict the lateral placement of different vehicles within a mixed traffic stream, a speed-based regression model was developed in the context of an undivided urban road [9]. Based on the model, the authors found that the lateral gap between opposite directional vehicles increases with the decrease in the physical size of the subject vehicles. Also, the lateral gap maintained between two vehicles can vary considerably with the speed of these vehicles [4]. Dibyendu and Chunchu [7] developed a cellular automata (CA)-based traffic simulation model to analyze the lateral gaps among vehicles moving in the same direction on a divided urban road. The authors found that a logistic distribution is the best-fitted to represent the lateral gap data. Besides, few researchers [13,14] realized the importance of prevailing traffic volume in determining the mean lateral placement of a vehicle category. If the traffic volume particularly towards the opposite direction increases, vehicles irrespective of their categories, shift away from the center of the road [13]. In contrast, Harish Kumar and Biswas [14] witnessed that the impact of traffic volume on the lateral placement is not similar for all vehicles rather, it varies suggestively depending upon the subject vehicle class. On the other hand, a number of studies further explored the influence of few other road elements like, the presence of edge and center line, horizontal curve, rumbled strips, shoulders etc. and highlighted their influences in determining the lateral placement of vehicles across the carriageway [15–20].

After reviewing the literature, it was sensed that a considerable research effort was devoted towards (i) the estimation of lateral placement of vehicles and the development of various lateral placement models and (ii) the impact assessment of different traffic parameters and other road elements (the presence of edge and centerline, horizontal curve, rumbled strips, shoulders, etc.) on the estimated lateral placement within a mixed traffic stream. However, the influence of road geometric factors like 'carriageway width' on the lateral placement was not given enough emphasis in former researches. Since the dynamics of lateral placement of vehicles on a narrow street is certainly different from that of a wider road, the carriageway width is expected to play a significant role in determining the lateral placement. Despite this, the carriageway width was never considered as one of the governing factors in any of those previous studies. Moreover, in a mixed traffic stream with loosely enforced lane discipline, a great deal of inconsistency is associated with choosing the lateral placement for a vehicle. This inconsistency is primarily governed by the subject vehicle type and the prevailing traffic and other conditions. But no investigation was carried out so far to quantify this 'inconsistency' associated with the lateral placement of vehicles. In this context, Inconsistency in Lateral Placement (ILP) is defined as the flexibility with which vehicles can swing in a transverse direction while moving along the road. This Inconsistency in Lateral Placement needs to be quantified for analyzing the weaving motion of vehicles within a mixed traffic stream. Therefore, the present study aims to quantify this 'Inconsistency' to categorize it into different levels and develop a suitable model which will be useful to predict ILP of a vehicle category for given traffic and other conditions. Further, this research intends to examine the sensitivity of ILP with the change in different traffic parameters (traffic volume, traffic composition, and directional split) and road geometric factor (carriageway width) on an undivided urban road.

2. Methodological framework

The present study is completed majorly in two distinct phases; (i) Collection of traffic and lateral placement data and (ii) Development of ILP model based on the collected data. The methodology adopted in each of these phases is discussed separately in the following sub-sections.

2.1. Methodology for data acquisition

The analysis of the present study is entirely governed by the field data collected at the mid-block segment of few undivided urban roads. The following criteria were adopted to select a mid-block location for the collection of required traffic and lateral placement data.

- The road section should be free from any longitudinal gradient, horizontal curvature, and any kind of surrounding hindrance like pedestrian movement, bus-stop, on-street parking, etc.
- The section should have a reasonably smooth pavement surface condition.
- The section should be free from access points and situated far away (at least 300 m) from the adjacent intersection on either side.

A high-resolution camera was mounted on the top of a 3.6 m tall camera-stand to record the traffic movements uninterruptedly on the selected mid-block urban road section. After the videography survey, the video files were taken to the laboratory and played on a computer screen to extract the required traffic and lateral placement data. Based on visual observation, vehicles were classified into seven categories; (i) Car, (ii) Motorized Bikes (2 W), (iii) Motorized three-wheelers (3 W), (iv) Light Commercial Vehicle (LCV), (v) Heavy Vehicles (HV), (vi) Bicycle (Bi) and (vii) Cycle Rikshaw (CR). Buses and trucks were considered under the HV category. Cycle rikshaw is a non-motorized three-wheeler. Following parameters under traffic data were extracted from the video files; (i) Traffic volume, (ii) Traffic composition and (ii) Directional split. Classified traffic volume i.e., the traffic volume under individual vehicle class is measured as the number

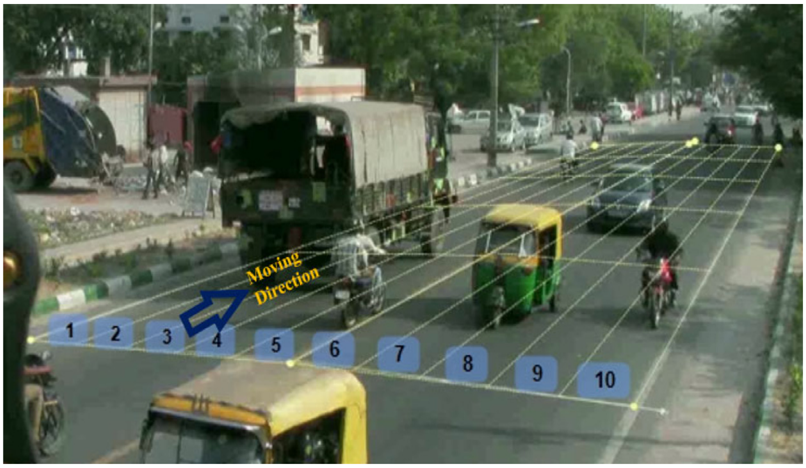


Fig. 1. Virtual grid lines to extract Lateral Placement data.

of vehicles crossing the road section within five-minute time intervals. The first two parameters (traffic volume and traffic composition) were obtained from the classified traffic volumes with respect to each time-interval. Directional Split (DS) in this study, was measured by considering it as the ratio of traffic volume in the 'subject direction' to the total traffic volume within a given time interval. 'Subject direction' in this study is referred to as the moving direction towards which the lateral placement is being measured. The lateral placement of a vehicle is defined as the transverse distance between the lateral position of the center of the vehicle and the edge of the carriageway in the subject direction. The information about the wheel position of vehicles is one of the prerequisites for the extraction of lateral placement data. To track the wheel position, the entire carriageway width was partitioned into ten equal segments by drawing virtual grid lines on the video files as shown in Fig. 1.

As may be seen in Fig. 1, segments were numbered from 1 to 10 from the left edge of the carriageway. The wheel position was carefully monitored as the vehicles were crossing the section. The segment number was recorded based on the wheel location, and the Lateral Position, (L. Pos.) in meter, was determined using the following formula.

$$L.Pos. = \frac{(N_s - 0.5) \times W}{T_s} \quad (1)$$

Where

N_s = segment number corresponding to a wheel position

CW = carriageway width (m)

T_s = total number of segments

The segment numbers corresponding to both wheels of the front axle were noted in the case of four-wheelers (cars, LCV and HV) and L. Pos. was determined accordingly using Eq. (1). The average L. Pos. corresponding to both wheels was considered as the lateral placement (LP) of the vehicle. However, in the case of two-wheelers (2 W and Bi) and three-wheelers (3 W and CR), the segment number corresponding to only the front wheel was noted and L. Pos. was calculated accordingly. LP of the vehicle, in this case, was taken the same as L. Pos. of the front wheel. Regarding Fig. 2, the lateral placement of a vehicle theoretically may vary within the range of [0, W] in the context of an undivided urban road. W is the carriageway width of the road. The heterogeneity of urban traffic coupled with poor lane-discipline instigates a high degree of inconsistency in the lateral placement of vehicles on a typical urban road of a developing country. With the aim of estimating the inconsistency in lateral placement, it was required to capture the deviation of lateral placement for different vehicles from the mean lateral placement as shown in Fig. 2.

Therefore, the inconsistency in lateral placement (ILP) was conceived as the standard deviation of LP values observed for a particular vehicle class within each five-minute time interval using the following formula.

$$ILP^j = \sqrt{\frac{1}{n}\sum_{i=1}^{n}\left(LP_i^j - \overline{LP}^j\right)^2} \quad (2)$$

Where

ILP^j = inconsistency in the lateral placement of vehicle class 'j' (m)

LP_i^j = observed value of lateral placement of vehicle class 'j' (m)

$\overline{LP}^j$ = mean lateral placement of vehicle class 'j' within five-minute time interval (m)

n = number of observations under a vehicle class 'j'.

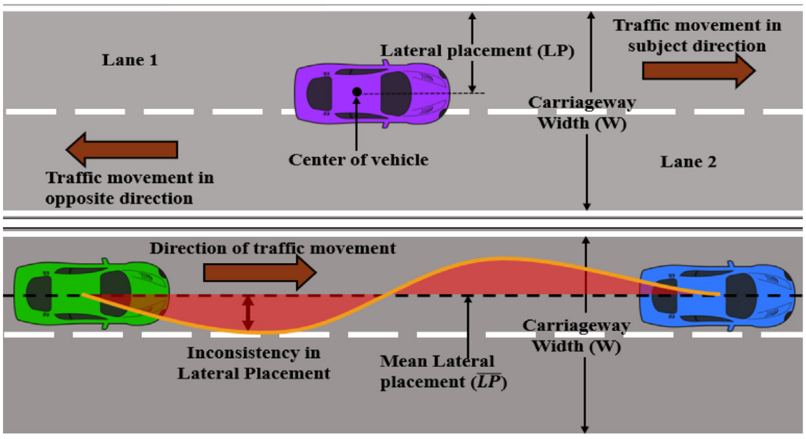


Fig. 2. Lateral Placement of a vehicle on the road.

2.2. Methodology for development of ILP model

ILP of a vehicle class is mainly governed by the prevailing traffic characteristics such as traffic volume along with its compositional characteristics and directional split if the road geometric factors and other conditions remain unchanged. In this regard, there was a need to consider these aforementioned traffic parameters while developing an ILP prediction model. Classified traffic volumes which are the product of total traffic volume and individual proportions in the traffic stream (as given in Eq. (3)) are competent to capture the traffic volume and its compositional aspects together [21].

$$\begin{bmatrix} Q_1 \\ Q_2 \\ Q_3 \\ \vdots \\ Q_{n-1} \\ Q_n \end{bmatrix} = \begin{bmatrix} P_1 \\ P_2 \\ P_3 \\ \vdots \\ P_{n-1} \\ P_n \end{bmatrix} \times [Q] \tag{3}$$

Where

$Q_i(Q_1, Q_2, Q_3 \ldots\ldots Q_n)$ = classified traffic volume (veh/h)
$P_i(P_1, P_2, P_3 \ldots\ldots\ldots P_n)$ = proportion of individual vehicle class (in a scale of 0 to 1)
Q = total traffic volume in both directions (veh/h)

However, the undivided urban roads in India are having diverse carriageway widths varying within a range of [5–10 m]. The characteristics of ILP are expected to differ on a narrower street as compared to a wider urban road. On this background, the classified traffic volumes (Q_i), directional split (DS), and carriageway width (CW) were taken as design variables in the construction of the model. On the other hand, ILP of individual vehicle class (ILP_i) was considered as the output variable to be predicted. As the class of the subject vehicle is a contributory factor towards determining ILP, there is a need to consider the ILP of each vehicle class as a separate output variable. If the number of vehicle classes observed in the mixed traffic stream is 'n', the number of design variables and the number of output variables will be 'n+2' and 'n' respectively. Hence, it was quite clear that the model to be developed for ILP prediction would be a multi-input–multi-output type. In this regard, the neural network-based approach is one of the efficient and commonly adopted machine learning tools for the construction of a multi-input–multi-output model. The structure of a neural network comprises three operating layers i.e., input, hidden, and output layers as shown in Fig. 3.

Each of these layers is further composed of several nodes. 'a_i', 'b_j' and 'c_i' represent the nodes of input, hidden and output layers respectively. These nodes are the basic functional units of a neural network. Qi, DS, and CW serving as input variables are taken in the input nodes 'a' and ILP_i, the output variables are obtained in the output nodes 'c'. Random weightage values are initially assigned to the input values which are being fed forward to the nodes of the hidden layer as shown in Fig. 4.

The random weightage values follow Xavier distribution which has the objective of keeping the variance of weightage values constant at each layer of the neural network. A bias, 'B' (either positive or negative) is applied to the functional

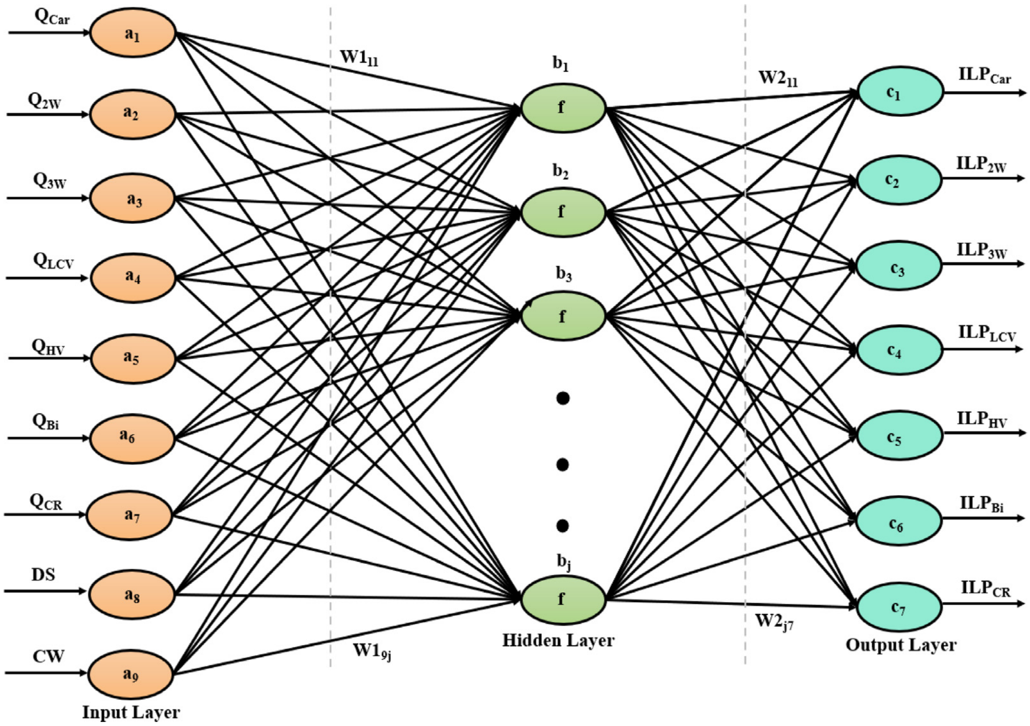


Fig. 3. Structure of a neural network.

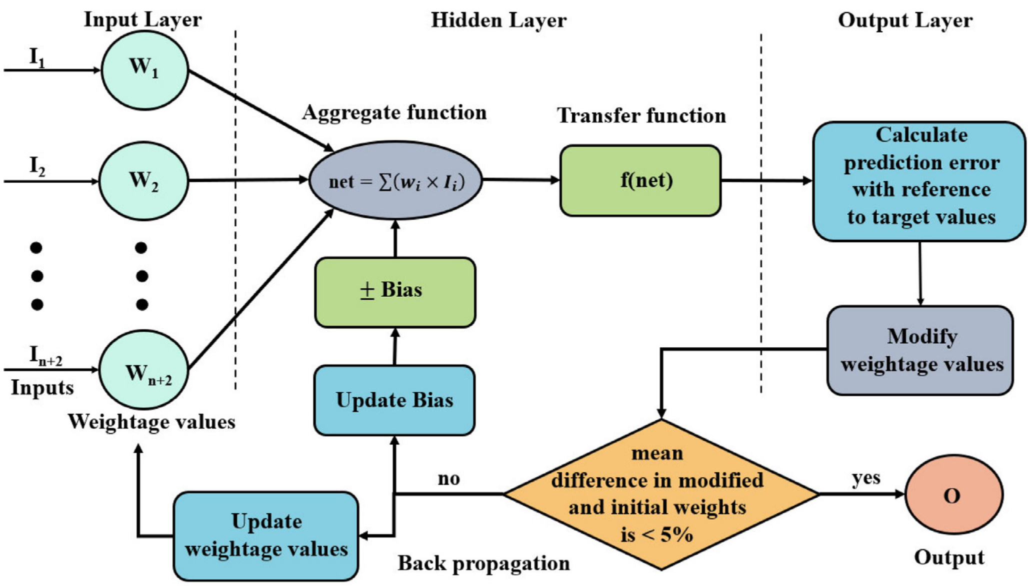


Fig. 4. Functioning of neural network-based model.

outputs as given in Eq. (4).

$$O_i = f\left(\sum (W_i \times I_i) \pm B\right) \tag{4}$$

I_i and O_i are the input and the output signal corresponding to neuron '*i*' respectively. 'W_i' is the weightage value corresponding to each connector connecting two consecutive layers. 'B' is the bias and '*f*' is the transfer function at the hidden layer. In this manner, the transfer function converts the signals coming from the input nodes into meaningful signals and feeds them to the output nodes. As mentioned before, the weighted values are initially obtained through

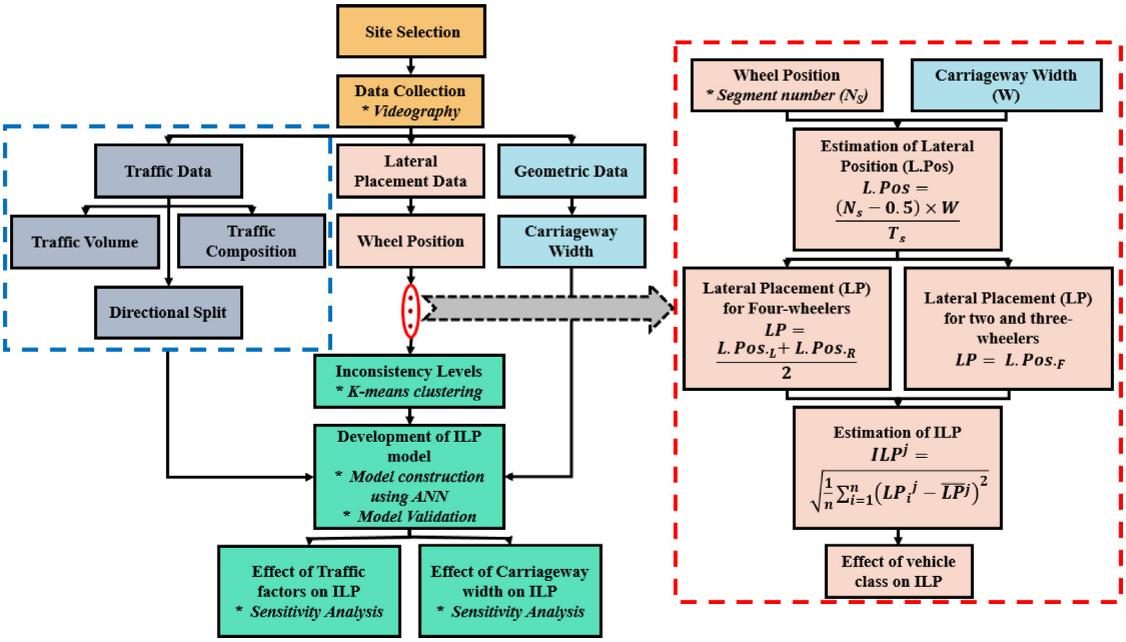


Fig. 5. Flow-chart demonstrating the methodology adopted in this research.

Table 1
Location and geometric details of selected road sections.

Road section	Name of the road	Carriageway width (m)	City	Latitude and longitude
Road section 1	Palam Road	9.0	New Delhi	28.5798 N 77.0961 E
Road section 2	Pashchim Marg	6.2	Chandigarh	30.7551 N 76.7554 E
Road section 3	Cross Road	5.5	Dehradun	30.3202 N 78.0488 E

Xavier distribution. In subsequent iterations, these weighted values along with biases are modified based on the prediction errors estimated at output nodes in the previous iteration. The prediction error is defined as the mean deviation observed for predicted values corresponding to its target values at the output layer. This way, the training process is repeated based on the modified biases and weightage values. This approach of modifying the initial weights and biases based on the prediction error is referred to as the backpropagation of neural networks. The bias is also updated similarly in the subsequent iterations. The training process is repeated until the mean difference (Δ) between the modified and the initial weightage values falls below 5%. Therefore, after the final iteration, the predicted values are obtained at output nodes.

In this way, a neural network was constructed to predict the ILP of a vehicle class for a given traffic and road geometric condition. However, before employing this model for ILP estimation, its efficiency was verified using an external validation test. After successful validation, a sensitivity analysis was performed on the model and the effects of traffic parameters (traffic volume, traffic composition, and directional split) and geometric parameter (carriageway width) on ILP of individual vehicle classes were examined.

The complete methodological framework adopted in this study is presented using a flow chart in Fig. 5.

3. Field data

Following the site selection criteria discussed in Section 2, three mid-block sections were chosen on two-lane two-way undivided urban roads in three capital cities of northern India viz. New Delhi, Chandigarh, and Dehradun. Location and geometric details of these study locations are given in Table 1.

The road sections were chosen from a wide range of carriageway widths of [5.5–9.0 m] to examine the influence of carriageway width on ILP. A videography survey was conducted for twelve hours (7 a.m. to 7 p.m.) on each of these sections and the required data were extracted from the video files following the procedure discussed in Section 2.1. Observed data showed a wide variation in traffic volume, traffic composition, and directional split on all road sections as given in Table 2. Cars and motorized bikes were observed sharing a substantial proportion of the urban mixed traffic.

Table 2
Details of Traffic data extracted for different road sections.

		% Car	% 2W	% 3W	% LCV	% HV	% Bi	% CR	Q (veh/h)	DS
Road section 1	Min.	21.70	26.73	1.33	0	0	2.26	0.37	1500	0.25
	Avg.	41.02	38.6	5.68	1.46	3.14	8.42	1.67	2700	0.50
	Max.	59.73	48.13	38.25	6.76	20.93	17.05	5.00	3750	0.75
Road section 2	Min.	20.49	36.05	3.57	1.27	0	1.68	0	1430	0.22
	Avg.	28.88	45.95	7.54	5.06	1.14	9.74	1.70	2080	0.50
	Max.	39.51	56.54	15.87	11.51	3.40	19.27	5.22	3360	0.78
Road section 3	Min.	17.00	54.32	0.93	0	0	0	0	648	0.26
	Avg.	25.21	64.38	4.25	1.58	0.12	4.17	0.29	1720	0.50
	Max.	33.97	72.04	9.25	5.75	1.00	19.00	1.80	2550	0.74

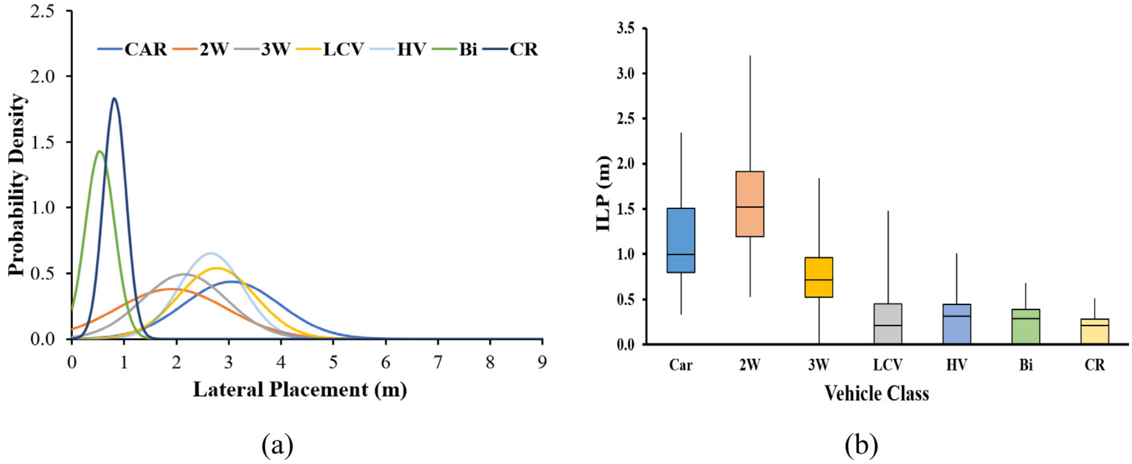


Fig. 6. The variation in (a) lateral placement profiles and (b) ILP data observed for different vehicle categories.

Apart from traffic data, the lateral placement of individual vehicles was extracted from the video following the procedure given in Section 2.1. LP of a vehicle is expected to fluctuate depending upon the change in traffic and geometric circumstances. Even under similar circumstances, different vehicle categories respond differently that justifies the consideration of vehicles under separate categories while analyzing the lateral placement behavior. The dissimilarity in lateral placement profiles for different vehicles within the same time interval is shown in Fig. 6a. For each 5-min time interval, the deviation of lateral placement values under a vehicle category from its section mean is captured by the parameter ILP. The variation in ILP observed for different vehicle categories is exhibited in a box-whisker plot (Fig. 6b).

The widespread lateral placement profile of 2 W in Fig. 6a indicates that the motorized bikes are the most inconsistent in choosing lateral placement among all vehicle classes. However, this inconsistency is quantified by ILP. As may be seen in Fig. 6b, the motorized bike has the highest average ILP (1.8 m) followed by cars (1.2 m) and 3 W (0.75 m). This high inconsistency of motorized bikes is subjected to their high maneuverability and smaller size. On the other hand, among the motorized vehicles, the heavy vehicle is the most consistent category with the minimum ILP of 0.35 m. Besides, non-motorized vehicles i.e., Bicycle and Cycle Rikshaw prefer to move closer to the edge of the carriageway in order to maintain a safe lateral gap from the fast-moving motorized vehicles. As a subsequence, non-motorized vehicles are quite consistent in choosing lateral placement resulting in low ILP values of 0.25 and 0.16 m respectively.

4. Inconsistency levels in choosing lateral placement

The present study classifies the observed range [0–3.2] of ILP among a few categorical levels for easy perception about the degree of inconsistency present in a traffic stream. Because it is important to perceive whether a certain value of ILP corresponds to a low or a high inconsistency. Therefore, an approach of K-means clustering was adopted to define the boundaries of different inconsistency levels. K-means clustering is an iterative algorithm, which groups the unlabeled dataset into a predefined 'k' number of clusters in such a way so that each dataset belongs to a group that has similar properties. Each cluster is associated with a centroid which was computed by taking the average of all ILP values that belong to that particular cluster. This algorithm aims to minimize the sum of squared distances between the ILP values and the cluster's centroid. Initially, the algorithm randomly takes the unlabeled ILP values as input and divides them among the pre-defined 'k' number of clusters. The ILP values nearer to a particular centroid were used to form a distinct cluster. The distance between each ILP and the different cluster centroids was calculated. If an ILP value was found closer

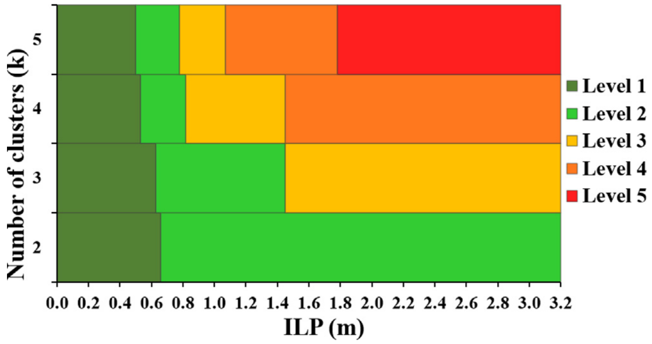


Fig. 7. Boundaries of different inconsistency levels.

Table 3
Assessment of quality of cluster formation based on Silhouette Index.

Range of Silhouette index	0.71–1.0	0.51–0.70	0.26–0.50	< 0.25
Interpretation	A strong structure has been found	A reasonable structure has been found	The structure is weak and could be artificial	No substantial structure has been found

Table 4
Recommended levels of Inconsistency in Lateral Placement and corresponding thresholds.

Inconsistency level in choosing lateral placement	Low	Medium	High
ILP threshold (m)	< 0.63	0.63–1.45	> 1.45

to another centroid as compared to its present centroid, the value was shifted to the corresponding cluster. In this way, the distribution of ILP among several clusters was rearranged and the centroid of each cluster was recalculated. This iteration process was continued until the maximum number of iterations is reached or there is no further need for rearranging ILP values (whichever earlier). Thus, the observed ILP data were categorized into different levels of inconsistency and the boundaries (upper and lower) for each level were estimated. Further, to find the optimum number of clusters, 'k' was varied from 2 to 5 and different sets of inconsistency clusters were obtained. Thus, four distinct sets of clusters were developed and each set took approximately 150 iterations to reach saturation. Boundaries of the clusters obtained for different values of k (2, 3, 4, and 5) are shown in Fig. 7.

Among these four distinct sets of clusters, the best cluster formation was chosen after the strength assessment. The strength of a cluster formation was assessed using the Silhouette technique. Silhouette value which indicates the degree of separation among clusters was estimated using Eq. (5).

$$\text{Silhouette value} = \frac{b^i - a^i}{\max(a^i, b^i)} \tag{5}$$

Where

b^i = average distance from all data points in the same cluster

a^i = average distance from all data points in the closest cluster

Silhouette value can vary within the range of [−1, 1]. '0' indicates that the sample is very close to the neighboring cluster. '1' indicates that the sample is far away from the neighboring cluster and '−1' indicates that the sample is assigned to the wrong cluster. Silhouette width is the average silhouette value of data points within the same cluster. Similarly, the average of Silhouette widths for all clusters is termed as Silhouette Index (SI). Higher SI indicates a stronger formation of clusters. Table 3 describes the quality of clusters based on the SI value [22].

Hence, SI was determined separately for different numbers of clusters (k = 2, 3, 4, and 5). As may be seen in Fig. 8, SI reaches its maximum value (0.62) when the number of clusters (k) was 3.

Therefore, three levels of inconsistency i.e., 'low', 'medium', and 'high', are proposed based on the boundaries obtained for the optimum number of clusters (k = 3) as given in Table 4. An ILP value less than 0.63 m is considered as 'low' inconsistency, between 0.63 and 1.45 is considered as 'medium' inconsistency and more than 1.45 is considered as 'high' inconsistency.

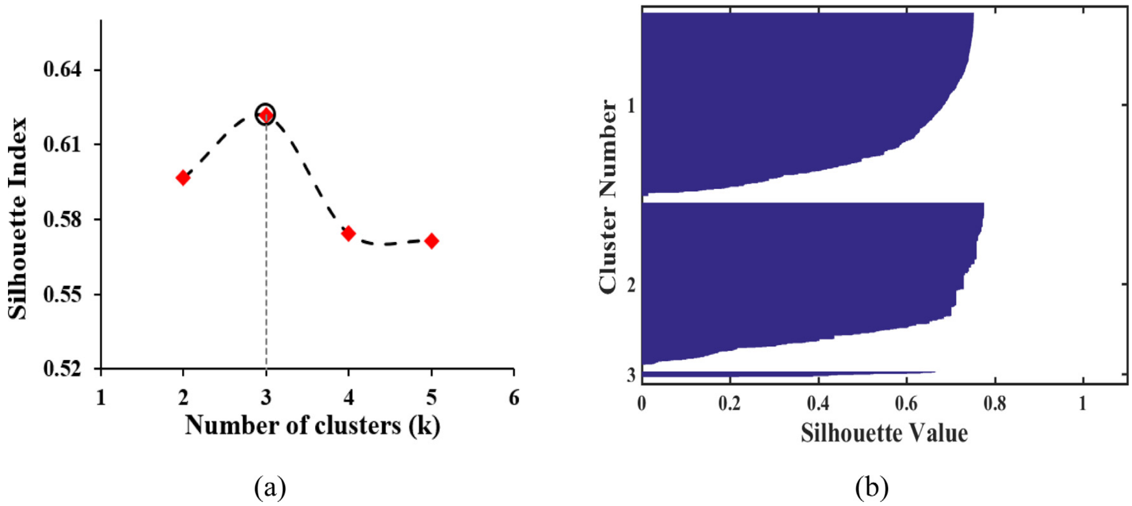


Fig. 8. Results of K-mean clustering showing (a) obtained SI values for two, three, four and five clusters and (b) SI-plot corresponding to three clusters.

Table 5
Data size for the construction of neural network.

Construction phase	Road section 1	Road section 2	Road section 3
Training	122	122	119
Testing	22	22	21
Total	144	144	140

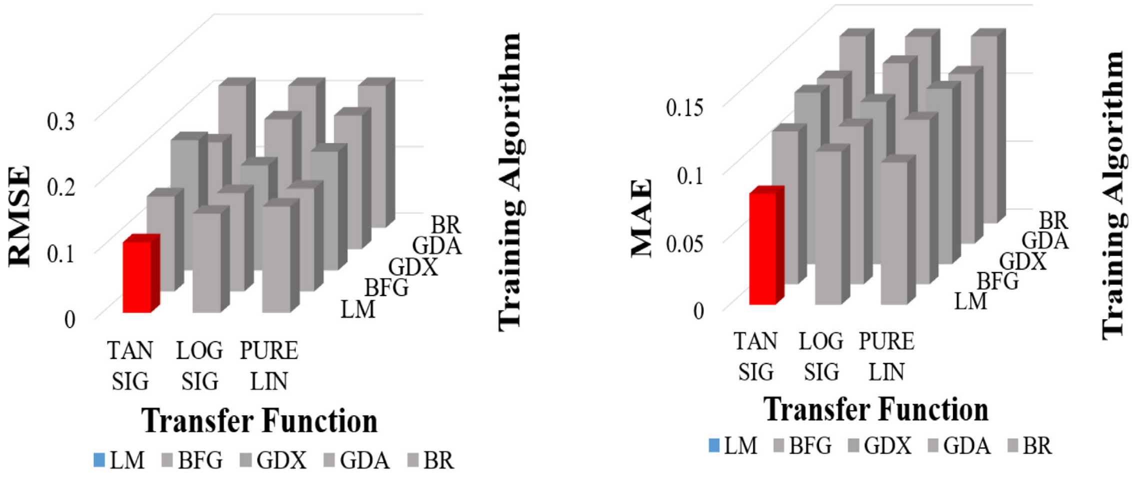
5. Development of neural network-based inconsistency model

5.1. Model construction

Traffic data collected at three road sections were utilized to develop separate neural networks for quantifying ILP. MATLAB software was used for the construction of the neural network. Since there were seven vehicle classes present in the mixed traffic, a nine-in–seven-out multilayer feed-forward neural network was formed by taking classified traffic volumes of seven vehicle classes along with the DS and CW as input variables. The size of data used in different phases of model construction is given in Table 5.

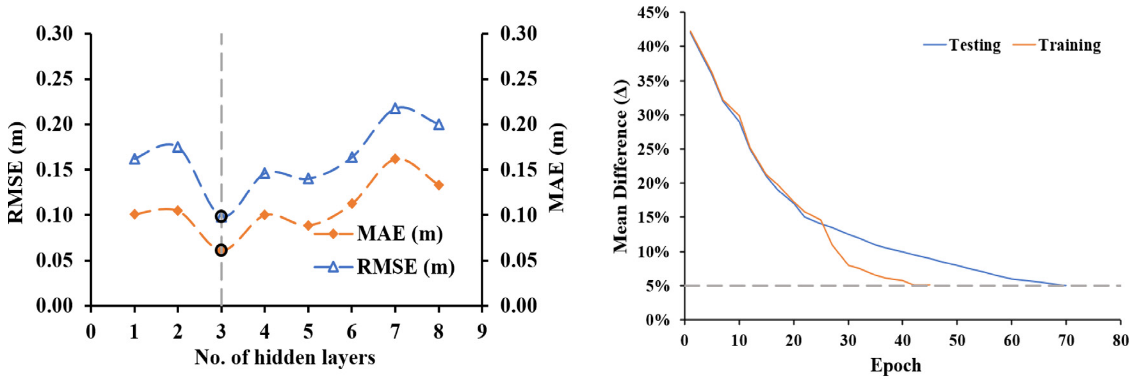
As may be observed in Table 5, 85% of data points were used in training the neural network and the rest 15% was utilized to test the performance of the developed network. Each row of the dataset consists of the following parameter corresponding to 5-min time interval; (i) ILP_{car}, (ii) ILP_{2w}, (iii) ILP_{3w}, (iv) ILP_{LCV}, (v) ILP_{HV}, (vi) ILP_{bi}, (vii) ILP_{CR}, (viii) Q_{car}, (ix) Q_{2w}, (x) Q_{3w}, (xi) Q_{LCV}, (xii) Q_{HV}, (xiii) Q_{bi}, (xiv) $Q_{CR,}$ (xv) DS, and (xvi) CW. A variety of training algorithms and transfer functions are available for developing a neural network. The present study attempted five training algorithms viz. (i) Levenberg Marquardt (LM), (ii) BFGS Quasi-Newton Backpropagation (BFG), (iii) Variable learning rate backpropagation (GDX), (iv) Gradient Descent with Adaptive learning rate (GDA) and (v) Bayesian Regularization (BR), and three transfer functions viz. (i) Tan Sigmoid (Tan Sig), (ii) Log Sigmoid (Log Sig), and (iii) Pure Linear (Pure Lin) for construction of the neural network. Hence, a total of 15 neural networks were constructed with all possible combinations of these five training algorithms and three transfer functions. Firstly, the neural network was trained based on the traffic, the road geometric and the lateral placement data collected from the field. However, to select the best combination of training algorithm and transfer function, two error parameters viz. (i) Root Mean Square Error (RMSE) and (ii) Mean Absolute Error (MAE), were employed. Errors estimated by these parameters corresponding to each possible combination of training algorithms and transfer functions were estimated and exhibited in a histogram (Fig. 9). As may be seen in Fig. 9, the neural network constructed based on the combination of Levenberg Marquardt backpropagation (LM) training algorithm and tan-sigmoid (Tan Sig) transfer function had the least error (RMSE of 0.10 m and MAE of 0.08 m) among all combinations in predicting the output variables i.e. ILP_i. Hence, this combination was considered for further analysis.

The number of hidden layers (H) was optimized based on the error yielded by the model in predicting the target values. For this, various LM-Tansig-based neural networks were constructed with H varying within an anticipated range of [1–8]. The accuracy of the model in predicting ILP, on each occasion, was assessed based on the error parameters. However, the minimum error (RMSE = 0.22 m & MAE = 0.16 m) was obtained when H is 3 as shown in Fig. 10a.



(a) (b)

Fig. 9. Errors of neural network in predicting ILP for different combinations of training algorithms and transfer functions based on (a) RMSE and (b) MAE.



(a) (b)

Fig. 10. Parameter adjustments showing (a) the optimized number of hidden layers and (b) the fall of mean difference with epoch.

Hence, an LM-Tansig network with three hidden layers was chosen for the prediction of ILP for a vehicle class. It is to be specified that in the construction of the above-said neural network, a gradual drop in the mean difference (Δ) between the updated and the initial weightage values was observed when the weightage values started converging as the computation progressed (as shown in Fig. 10b). The iteration was stopped when Δ dropped below the threshold limit (5%) for both training and testing phases. Thereafter, 15% of observed data that were not utilized in the training phase, were considered for testing the model. The prediction errors i.e. the difference between the observed and the predicted ILP obtained for each vehicle category in the testing phase are reported in Table 6. The constructed model was then taken to the external validation test.

5.2. Model validation

Before utilizing the model in assessing the characteristics of ILP under mixed traffic conditions, it was required to verify the efficiency of the model by external validation based on a new set of data. Therefore, the traffic, lateral placement, and road geometric data were collected for three hours (7 am to 10 am) at a new section on Subhash Road, Dehradun, India. This road section satisfies all of the predefined site selection criteria and is having a carriageway width of 7.0 meters which is dissimilar to the carriageway width of any previously considered road sections. The classified traffic volumes (Q_i), the directional split (DS), and the carriageway width (CW) measured at Subhash Road were fed as input signals

Table 6
Prediction errors yielded by different approaches in testing and validation processes.

Approach	Phase	Prediction error	Vehicle class							Overall
			Car	2W	3W	LCV	HV	Bi	CR	
ANN-based model	Model testing	RMSE (m)	0.06	0.15	0.14	0.08	0.09	0.05	0.03	0.09
		MAE (m)	0.04	0.12	0.10	0.06	0.07	0.03	0.01	0.06
	Model validation	RMSE (m)	0.16	0.23	0.15	0.23	0.12	0.08	0.05	0.14
		MAE (m)	0.12	0.16	0.12	0.13	0.10	0.07	0.03	0.10
GPR-based model	Model validation	RMSE (m)	0.16	0.23	0.25	0.39	0.23	0.20	0.07	0.22
		MAE (m)	0.14	0.20	0.18	0.28	0.15	0.15	0.04	0.16

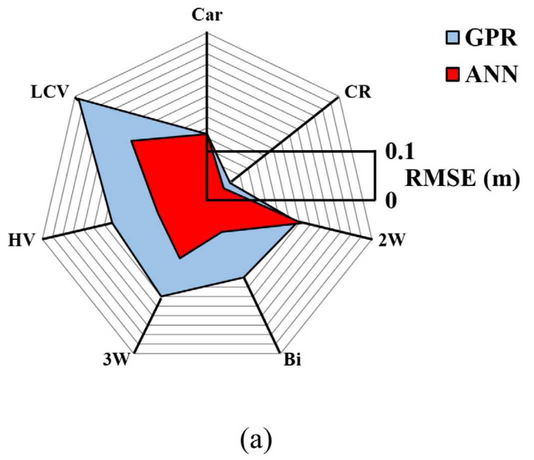


Fig. 11. Prediction errors, in terms of (a) RMSE and (b) MAE yielded by different models in the external validation.

in the previously developed neural network. Therefore, ILP values predicted by the model for each vehicle class were noted and considered for comparative assessment. ILP values for different vehicle classes observed at Subhash Road were compared with these predicted ILP values. The deviation of the predicted ILPs from the observed values was measured using two error parameters viz. (i) Root Mean Square Error (RMSE) and (ii) Mean Absolute Error (MAE). As may be seen in Table 6, the maximum and the overall prediction error obtained in the validation phase are respectively 0.23 m and 0.14 m (RMSE) which are only 7.2% and 4.4% of the observed ILP range [0–3.2 m].

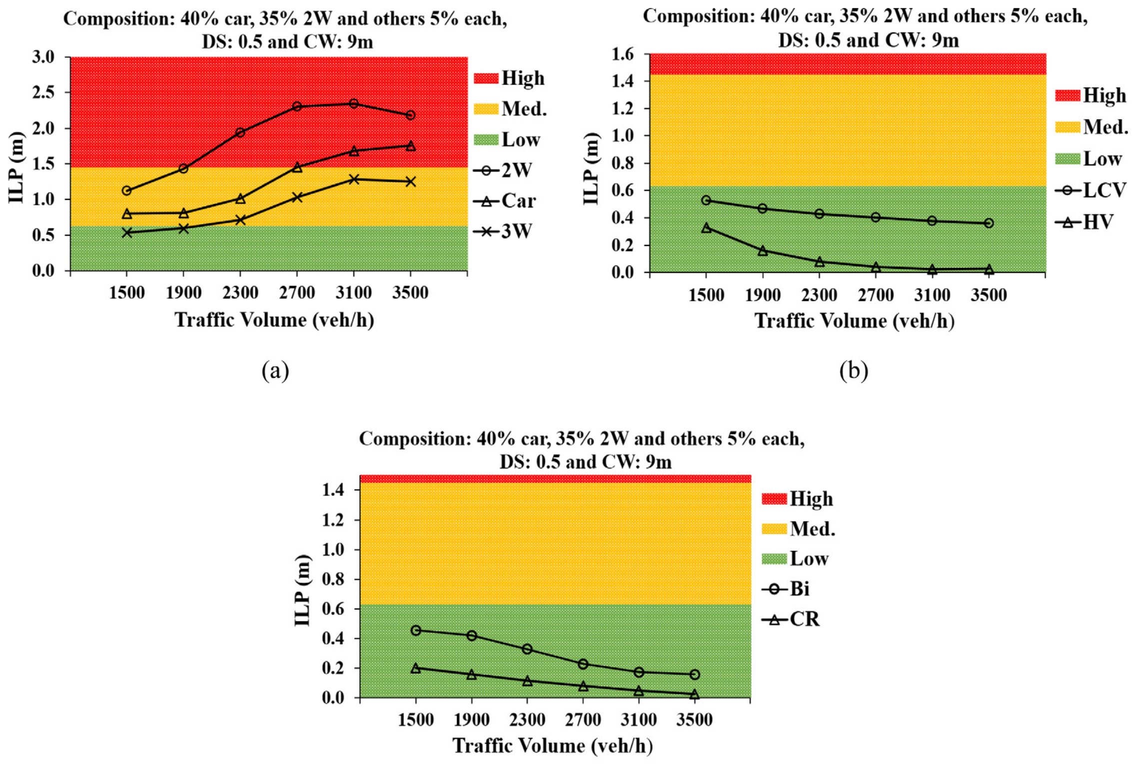
This result ensures the efficiency of the developed model in predicting the ILP of a vehicle class at any given traffic and road geometric condition. Further, the performance of this model was compared with another state-of-the-art data-driven approach called Gaussian Process Regression (GPR). Seven distinct GPR-based models were developed to predict the ILP of individual vehicle classes. Later, in the external validation, these models were utilized to predict the ILP based on Qi, DS, and CW observed at Subhash Road, and accordingly, the prediction errors were estimated. Table 6 shows that the prediction error yielded by the GPR model was thoroughly found either equal or higher than the ANN model. The radar chart (Fig. 11) shows the visual comparison of errors yielded by these two distinct sets of ILP models. Hence, the developed Neural Network model was finalized and further considered for exploring the dynamic aspects of ILP.

6. Dynamic aspects of ILP

Inconsistency of vehicles in choosing the lateral placement is not a static phenomenon, rather, it is expected to fluctuate widely depending upon the prevailing traffic and other conditions. A sensitivity analysis was carried out in this study to examine the effects of traffic volume, traffic composition, directional split, and carriageway width on the ILP of a vehicle class. Results obtained in each sensitivity analysis are reported separately in the following sub-sections.

6.1. Effect of traffic volume on ILP

To examine only the effect of total traffic volume, the classified traffic volumes in the neural network were varied judiciously in such a pattern so that the traffic composition could be kept constant at predefined values (40% car, 35% 2 W, and others 5% each) and the traffic volume could be varied within the observed range [1500–3700 veh/h] gradually in a systematic manner. The overall mean of the observed traffic composition (adjusted to its nearby suitable values) was considered as the predefined values. The directional split was fixed at its overall mean of 0.5. The carriageway width, on



(a) (b) (c)

Fig. 12. Effect of traffic volume on ILP of (a) car, 2 W, and 3 W, (b) LCV and HV, and (c) Bi and CR.

the other hand, was fixed at 9 m. Therefore, the change in ILP values predicted by the model was monitored with the increase in traffic volume as shown in Fig. 12.

There are three types of vehicle classes in the traffic mix (car, 2 W, and 3 W) which are small in size, highly maneuverable, and having moderate to high-speed profiles. The overtaking tendency of these vehicles (car, 2 W, and 3 W) increases with the increase in traffic volume. Subsequently, the increase in overtaking maneuvers increases the inconsistency in the lateral placement of these vehicle classes. However, after a certain point (3000 veh/h), further increase in traffic volume makes the opposite directional traffic hinder the overtaking opportunities. Due to this, ILP for cars, 2 W, and 3 W initially increase but after a certain point, no considerable change in ILP is observed as the traffic volume increases in the traffic stream. On the other hand, heavy vehicles (HV) and light commercial vehicles (LCV) are generally the side-givers who allow other fast-moving and high-maneuverable vehicles to overtake them under mixed traffic conditions. Hence, the increase in traffic volume reduces the available lateral gap for these vehicles to maneuver. As a result, the margin of swinging in the transverse direction for these vehicles is now restricted to a narrower width on the carriageway. It further leads to the reduction in the inconsistency of lateral placement for HV and LCV. However, the reduction rate for HV is more intense due to its larger size and inferior maneuverability as compared to LCV. Similarly, the increase in traffic volume makes the non-motorized vehicles (Bi and CR) more consistent in choosing the lateral placement closer to the edge of the carriageway as an attempt to maintain a safe lateral gap from other motorized vehicles. Thus, ILP of Bi and CR drops gradually with the increase in traffic volume within the mixed traffic stream.

6.2. Effect of traffic composition on ILP

In the second phase of sensitivity analysis, the classified traffic volumes in the neural network were varied judiciously in such a pattern so that the effect of traffic composition on ILP could be captured. In this regard, the traffic volume and DS were kept constant at its observed mean of 2500 veh/h (adjusted to the nearby suitable value) and 0.5 respectively. The carriageway width was fixed at 9 m. The proportions of car and 2 W which account for approximately 80% of the vehicle population, were varied simultaneously within the range of 0.30 to 0.75 and 0.20 to 0.45 respectively in a systematic manner. At the same time, the individual proportions of all other vehicle classes were fixed at 0.05. Based on these input values of classified traffic volumes and DS, the change in ILP for different vehicles predicted by the neural network was recorded and shown in Fig. 13. The ILP of cars, 2 W and 3 W increases gradually as the proportion of cars increases in

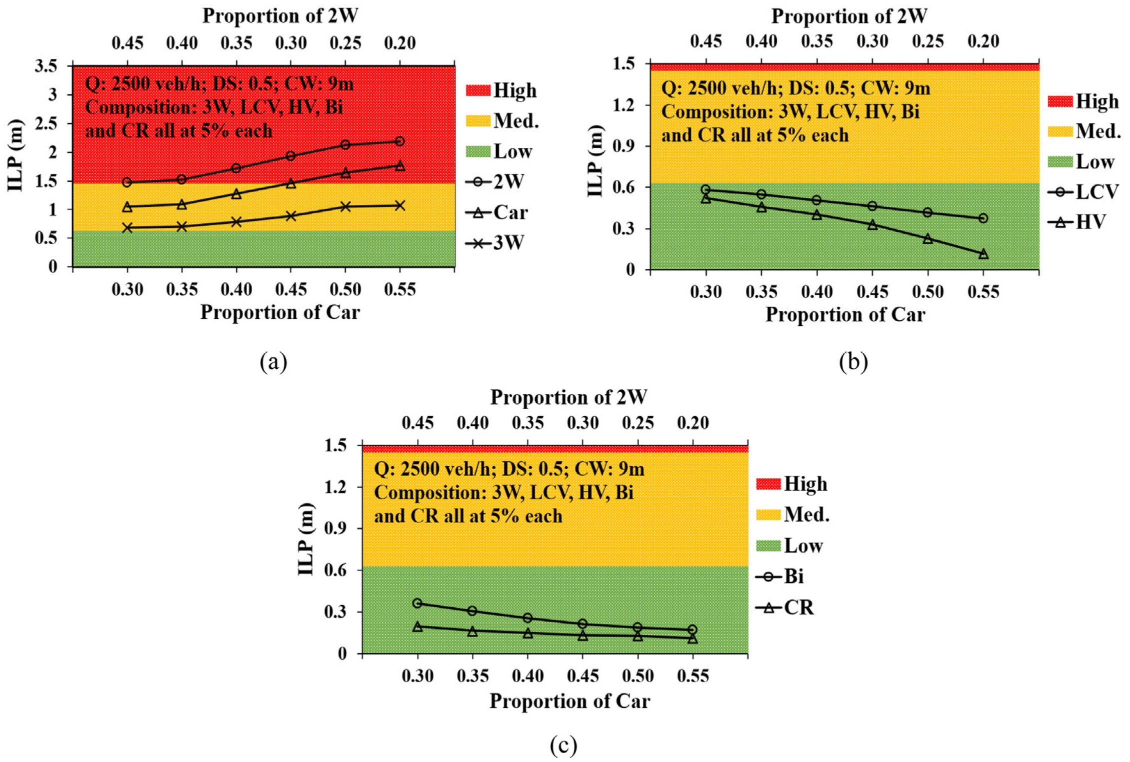


Fig. 13. Effect of traffic composition on ILP of (a) car, 2 W, and 3 W, (b) LCV and HV, (c) Bi and CR.

the traffic stream. With the increase in the proportion of cars and a simultaneous decrease in the proportion of 2 W, the two-wheelers get replaced with motorized cars in the traffic stream at constant traffic volume. This increases overtaking operations in the traffic stream thus, ILP of overtaking vehicle classes i.e. car, 2 W, and 3 W increases, and ILP of overtaken vehicle classes i.e. HV and LCV decreases gradually. Similarly, Bi and CR shift closer to the edge of the carriageway to safeguard themselves from other motorized vehicles. Thus, ILP of Bi and CR also drops as the proportion of cars increase in the traffic stream.

6.3. *Effect of directional split on ILP*

In the next phase, the traffic volume and its composition were kept constant at their observed means, and DS was varied gradually within the observed range of 0.25 to 0.75. The variation of ILP for different vehicle classes yielded by the neural network is shown in Fig. 14. In the case of vehicle classes with relatively smaller size and good maneuverability like cars, 2 W and 3 W, an overall increasing trend of ILP was observed with the gradual increase in the directional split. However, the rate of increase was insignificant up to a DS of 0.6 beyond which, an acute increase in ILP (nearly 0.85 m per 0.1 increase in DS) was observed. It is because the increase in DS represents the increase in the traffic volume in the subject direction replacing the opposite directional traffic. Thus, the demand for lateral spaces in the subject direction increases, and the fast-moving and high maneuverable vehicles (like cars, 2 W and 3 W) start shifting towards the adjacent lane in the absence of considerable traffic volume in the opposite direction. This eventually increases the ILP of these vehicle classes. A similar incremental trend of ILP was observed for LCV class although the rate of increase was nominal as compared to other vehicles. On the other hand, despite the increase in DS towards the subject direction, larger-sized vehicles like HV cannot perform much shifting operations towards adjacent lanes, unlike the aforementioned vehicle classes. Instead, they tend to move within a definite lateral space and allow other fast-moving vehicles to shift right towards the adjacent lane. As a result, the ILP of HV decreases with the increase in DS if other factors like traffic volume and its composition remain unchanged in the traffic stream. Besides, ILP of non-motorized vehicles (Bi and CR) show minor deviation with the change in DS as they move close to the left edge of the carriageway and remain unaffected by the ongoing shifting operations of other vehicles towards the adjacent lane.

6.4. *Effect of carriageway width on ILP*

The previous sub-sections have emphasized the effects of change in traffic parameters (traffic volume, traffic composition, and directional split) on the ILP of a vehicle class. In order to examine the effect of carriageway width on ILP, the

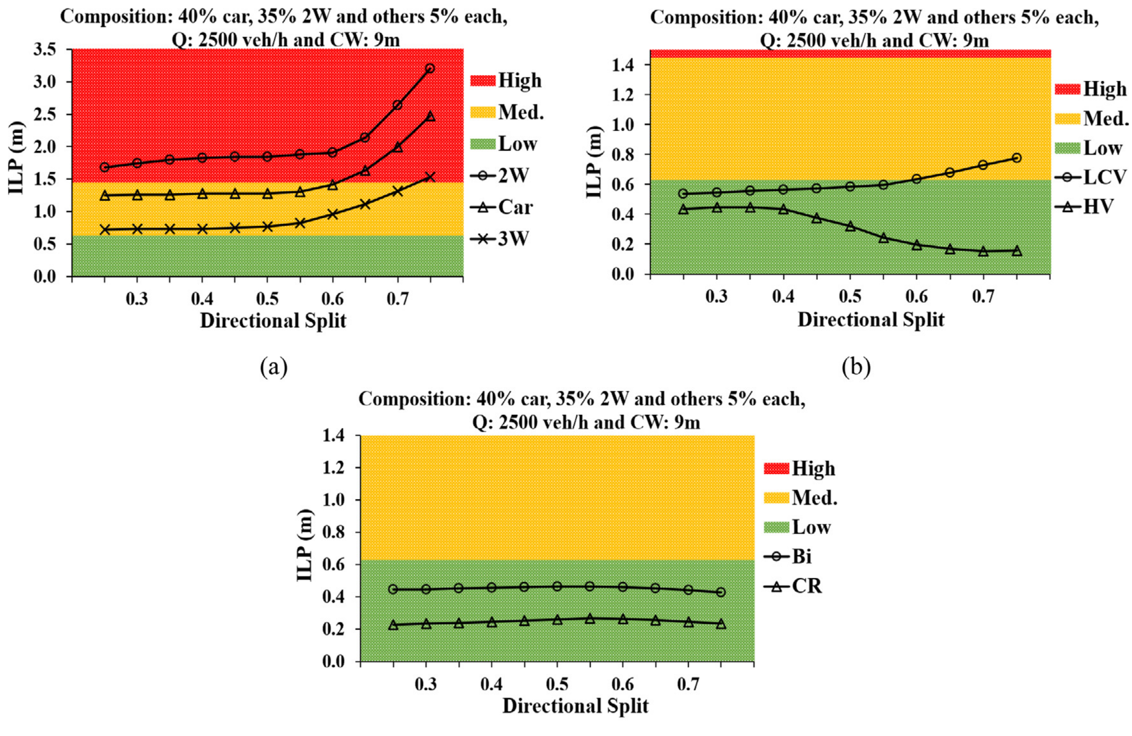


Fig. 14. Effect of directional split on ILP of (a) car, 2 W, and 3 W, (b) LCV and HV, (c) Bi and CR.

traffic volume, its composition, and DS were kept constant at their observed means (2500 veh/h; 40% car, 35% 2 W, others at 5% each; and 0.5 respectively). The CW was varied gradually within the observed range of 5.5 to 9 m. Therefore, the variation in ILP yielded by the neural network was plotted in Fig. 15 for comparative assessment.

As may be seen, ILP increases as the carriageway width increases irrespective of the vehicle class. This trend can be justified in the following manner. A wider carriageway provides additional flexibility to a vehicle for swinging laterally and choosing its lateral placement. This additional flexibility brings an extra inconsistency in lateral placement among vehicles specifically, in a circumstance where heterogeneous vehicles are sharing the common carriageway with loosely-enforced lane discipline.

7. Conclusions

This paper forwards a neural network-based approach for quantifying the degree of inconsistency associated with the lateral placement of different vehicle classes. The neural network-based Inconsistency in Lateral Placement (ILP) model and the graphs (Figs. 11–14) developed in this study are useful to predict the inconsistency in the lateral placement of different vehicle classes under given traffic and geometric conditions on a two-lane undivided urban road serving both directional traffic. The present study also suggests three inconsistency levels (high, medium, and low) which will be extremely helpful to perceive the degree of aforementioned inconsistency easily. Further, the outcome of this research can be useful to track the wheel positions of different vehicles within a mixed traffic stream and accordingly, to identify the distressed portion of the pavement. Some of the significant findings of this research are given below.

- Bikes are the most inconsistent category in terms of choosing lateral placement among motorized vehicles with a mean ILP of 1.8 m followed by cars (1.2 m), three-wheelers (0.75 m), Light Commercial Vehicles (LCVs) (0.45 m), and heavy vehicles (0.35 m). Heavy vehicles have the lowest ILP value which makes them the most consistent motorized vehicle class. On the other hand, among non-motorized vehicles, both bicycles (0.25 m) and cycle rickshaws (0.16 m) are quite consistent in choosing lateral placement since they tend to move closer to the left edge as an attempt to avoid interactions with motorized traffic.
- As per the criteria recommended in this paper for assessing inconsistency level, an ILP value less than 0.63 m is considered as ‘low’ inconsistency, between 0.63 and 0.82 m is considered as ‘medium’ inconsistency, and higher than 0.82 m is considered as ‘high’ inconsistency.

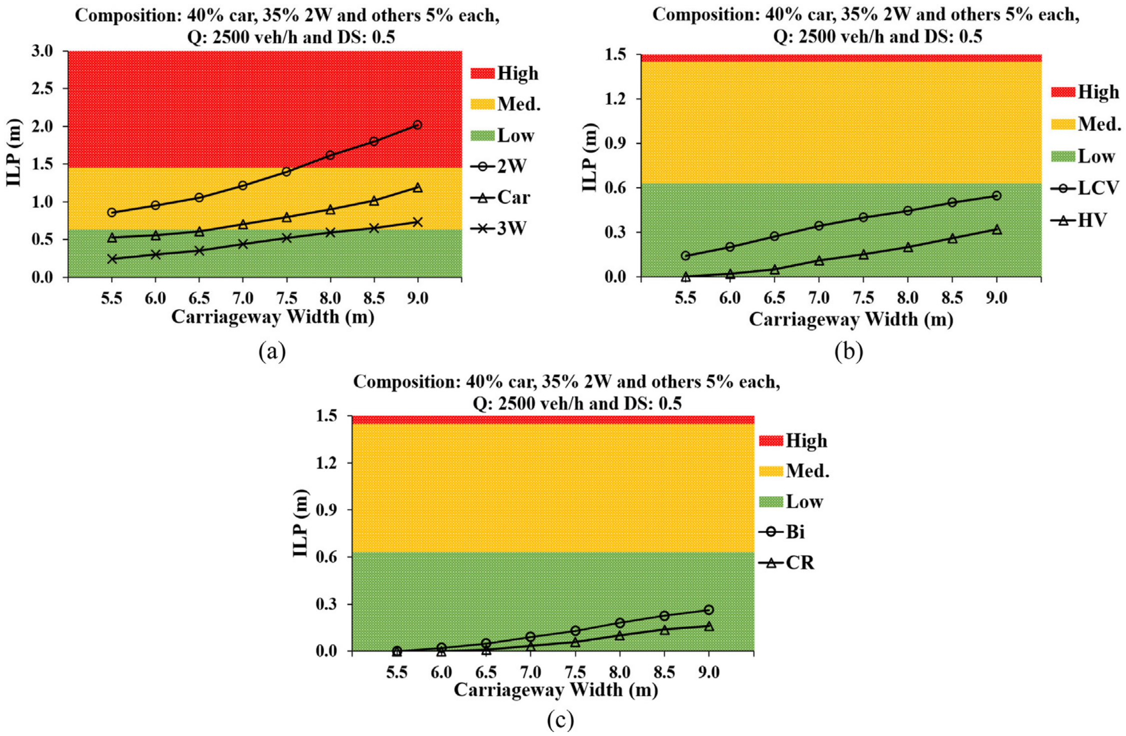


Fig. 15. Effect of carriageway width on ILP of (a) car, 2 W, and 3 W, (b) LCV and HV, (c) Bi and CR.

- A prominent influence of traffic volume, traffic composition, and directional split on ILP was noticed for most of the vehicle classes. In fact, the change in any of these parameters (traffic volume or traffic composition or directional split) has the potential to take the ILP to another inconsistency level singlehandedly, explicitly for high-speed and high maneuverable motorized vehicles like cars, bikes, and three-wheelers (refer to Figs. 11–13). ILP for these vehicles initially increases with the increase in traffic volume on the road. However, beyond a certain point (3000 veh/h), ILP becomes almost constant and therefore, the insignificant influence of traffic volume on ILP was observed. In the case of heavy vehicles and LCV, ILP decreases gradually when traffic volume increases up to 3000 veh/h beyond which, it becomes almost constant. For non-motorized classes (Bicycle and cycle rickshaw), a small but gradual decrease in the ILP was observed.
- An increase in the proportion of cars in the traffic stream leads to an increase in ILP for cars, motorized two-wheelers, and three-wheelers due to the increase in the frequency of overtaking operations. As a response to a similar change in traffic composition, exactly the opposite trend was observed for heavy vehicles and LCVs since the ILP of these vehicles drops gradually. ILP of non-motorized vehicles also shows a small reduction with the increase in the proportion of cars in the mixed traffic stream.
- For high-maneuverable vehicles, the directional split has a substantial impact only when it exceeds 0.6. Beyond this point, high-maneuverable vehicles (cars, motorized two-wheelers, and three-wheelers) start occupying some widths of the adjacent lane in absence of considerable traffic volume towards the opposite direction. It eventually results in a sudden upsurge of ILP for these vehicles. Contrariwise, the ILP of heavy vehicles decreases gradually with the increase in directional split up to 0.6, and then it becomes almost constant. On the other hand, non-motorized vehicles remain unaffected by the change in the directional split in the traffic stream.
- A sensitivity analysis performed on diverse carriageway widths revealed that the inconsistency in choosing lateral placement is more intense for wider roads irrespective of vehicle class if other traffic parameters remain constant. It is owing to the fact that a wider carriageway provides additional flexibility to a vehicle for swinging laterally while choosing its lateral placement resulting in a higher ILP value. Thus, with the increase in the carriageway width from 5.5 to 9 m, the ILP increases up to 1.2 m for vehicles having high inconsistency (car, 2 W and 3 W), and about 0.5 m increase in ILP is observed for other vehicle classes (HV, LCV, Bi and CR).

CRediT authorship contribution statement

Bhavna: Software, Validation, Formal Analysis, Investigation, Data curation, Writing – original draft. **Subhadip Biswas:** Conceptualization, Methodology, Writing – review & editing, Visualization, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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