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Estimating Lateral Placement and Lane Indiscipline of Urban Mixed Traffic of Developing Country: An ANN Assisted Approach

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Abstract

Information of lateral placement and lane indiscipline are useful in simulation of a mixed traffic stream and identifying the distressed portion of a pavement. In spite of these utilities, inadequate investigation was made to estimate the lateral placement of vehicles under prevailing traffic conditions. In a typical mixed traffic situation, vehicles having different static and dynamic characteristics take any lateral gap across the carriageway left empty by other surrounding vehicles and move in an untidy manner. It leads to variation in lateral placement of vehicles governed by the subject vehicle type. This paper explores the potential factors that influence lateral placement of vehicles and presents an Artificial Neural Network based approach to quantify lateral placement and lane indiscipline in context of undivided urban roads. Further, sensitivity analysis revealed how different traffic parameters like traffic volume, traffic composition and directional split influence lateral placement and lane indiscipline of a vehicle category.

Keywords: Lateral placement; Lane Indiscipline; Traffic Volume; Traffic Composition; Directional Split.

Introduction

Lateral placement (LP) represents the transverse position of vehicle on the carriageway. For undivided road, LP is measured as the distance from the left edge of carriageway in case of left-

hand driving. But for divided road, it is measured either from the edge or the median of the road. On majority of urban roads specifically in developing countries, there is no provision of segregation of lanes for fast and slow moving vehicles. Vehicles irrespective of categories share the common right-of-way even at high traffic volume condition. This not only instigates congestion on roads but also compromises safety of road users. Apart from these, tendency of motorists often is to take any suitable lateral gap available in front of the vehicle across the carriageway. It results in a wide variation in LP of vehicles and eventually a poor lane discipline. Information of lateral placement and lane indiscipline (LI) are very crucial as these are pre-requisites in some important investigations. For example, information of lateral placement is helpful to identify the wheel positions of vehicles on a carriageway. Central tendency of wheel positions is used to locate the strained portions on the pavement (Das et al. 2016). The information of lateral placement of different vehicles is a prerequisite for simulating a mixed traffic stream in a developing country where lane discipline is weakly followed (Mahapatra and Maurya 2015). Also, study of LP and the movement of vehicles on the road find important applications in accident analysis, geometric design of road, traffic control and management etc. Because of these utilities, investigation on lateral placement and lane indiscipline of vehicles has gained importance over time.

A number of techniques were adopted previously by researchers to estimate LP of vehicle. Dey et al. (2006) and Balaji et al. (2013) pasted cloth tapes on the pavement to divide the carriageway width into a number of segments having equal widths during field data collection via videography. Lindheimer et al. (2017) drew few parallel lines on a transparent sheet. The sheet was kept on the computer screen in such a manner so that the parallel lines could divide the carriageway width into a given number of segments when the video of traffic

movements was played on the computer. Few studies (Mahapatra and Maurya 2015; Balaji et al. 2013; Dey et al. 2006; Lindheimer et al. 2017) witnessed LP of vehicle may vary with the category of subject vehicle. It was observed that fast moving vehicles prefer to move on median lane rather than shoulder lane. On the other hand, the heterogeneity of mixed traffic may have a significant influence on the lane indiscipline of vehicles. In this regard, few studies (Munigety and Mathew 2016; Papathanasopoulou and Antoniou 2018; Papathanasopoulou and Antoniou 2019) adopted virtual lane-based approach in order to estimate the heterogeneity among vehicles in the mixed traffic stream. Further, few researchers extended the investigation towards estimating the influences of some governing factors (traffic parameters and road geometric factors) on LP of vehicle. Among road geometric factors, influences of lane width and shoulder width on LP of vehicles were examined. It was thoroughly reported in literature (Lindheimer et al. 2017; Mecheri et al. 2017) that vehicles are shifting away from the edge of carriageway as lane width increases. On the other hand, with the increase in shoulder width, vehicles shift laterally towards the edge of carriageway (Van Driel et al. 2004; Mecheri et al. 2017; Lindheimer et al. 2017). Also, treatments like installation of rumble strips, have impacts on lateral placement of vehicles (Porter et al. 2004; Gates et al. 2012). Traffic flow parameters which describe the traffic condition prevailed on a road, may have significant contribution in determining the lateral placement of vehicle. Triggs (1980) witnessed that the presence of vehicles in the neighboring-lane forces the subject vehicle to shift towards the other direction laterally. Balaji et al. (2013) found a strong correlation between LP and the speed of subject vehicle. Vehicles shift away from the edge of carriageway as speed increases. However, the influences of other important traffic parameters such as traffic volume, traffic composition, directional split (for undivided road) etc. are yet to be examined. It is to be mentioned here that

no investigation on quantification of lane indiscipline was reported till date to the best of authors's knowledge. On this background, the present research aims a) to present a suitable methodology to estimate LP and LI of mixed traffic, b) to examine how LP and LI vary with the subject vehicle type and c) to assess the influences of traffic flow parameters i.e. traffic volume, traffic composition and directional split on LP and LI of individual vehicles. However, under the scope of this study, the present research is only contextual to two-lane undivided urban streets.

Research Methodology

The primary aim of this paper is to develop a model which can predict LP of vehicles for a given traffic condition. LP obtained by this model is further used to estimate LI associated with the mixed traffic flow. Hence, the present investigation is divided into two phases; a) development of lateral placement model and b) estimation of lane indiscipline. Methodologies followed in each of these phases are described below.

Methodology for Development of Lateral Placement Model

Lateral placement of a vehicle is defined as the distance between the lateral position of centre of that vehicle across the carriageway and the adjacent edge of the road in the moving direction. The direction of traffic movement at which LP is being measured is referred as 'subject direction' in this study. Traffic volume, traffic composition and directional split which describe the traffic condition on an undivided road, have significant influence on LP of vehicles. Directional split (DS) in this study is defined as the ratio of traffic volume in the subject direction to the total traffic volume. Classified traffic volumes (Q_i) were taken as design

variables since it captures both traffic volume and its composition characteristics (Biswas et al. 2017a). Also, it was realized that the category of subject vehicle may have a significant role in determining LP. Hence, consideration of LP separately for each vehicle category would be more meaningful. To this end, a LP model was developed for each vehicle category considering classified traffic volumes and directional split as input variables.

Artificial neural network (ANN), a computational technique was used in this study to develop a multi-input-multi-output model which predicts LP of a vehicle for a given combination of traffic volume, traffic composition and directional split. ANN is a kind of Artificial Intelligence technique whose structure is enhanced by structure of neurons in the human brain (Uhrig 1995; Haykin 2009). Today, ANN is a very popular tool which is used in analyzing many complex problems in various disciplines such as medical diagnosis (Ganesan et al. 2010), pattern recognition (Silva et al. 2006; Sthapak et al. 2013), coastal engineering (Dwarakish et al. 2013), 3D construction (Tam and Tong 2003) etc. These network are based on the collection of connected units i.e. neurons. These neurons are the core processing unit of the network. These connected neurons transmit signals from one neuron to another and the receiving neuron process the signal and transmit further (Yegnanarayana 2009). Functioning of an ANN model is largely governed by the inter-connected units i.e. neurons which are the core processing elements proficient in performing massively parallel computations for large data processing. ANN models are desirable due to some of its functional characteristics. These are nonlinearity, adaptivity, fault tolerance, uniformity of analysis and self-organization. Also, ANN as a methodology offers flexibility to choose suitable training algorithm and activation function. In ANN models, the user does not need to assume the trend of relationship (linear, polynomial, logarithmic, exponential etc.) prior to model construction unlike conventional approaches (regression). ANN approach

was proved more accurate and also requires less volume of data for model construction as compared to other conventional methods (Back et al. 1996; SubbaNarasimha et al. 2000; Heiat 2002). For these reasons, ANN has gained more popularity than conventional multiple regression analysis in recent times. Fig. 1a shows the basic structure of a multi-input-multi-output neural network.

Fig. 1. a) Basic structure and b) iteration process to update weightage values of neural network

As may be seen in Fig. 1a, the network consists of three functional layers i.e. input, output and hidden layer where a_i , b_i and T_i represent the nodes of input, output and hidden layer respectively. In this case, Q_i and DS serve as input variables whereas lateral placements (LP_i) of individual vehicle category were considered as output variables of the network as shown in Fig. 1a. f_i denotes the transfer function at hidden layer and w_i is the weightage value corresponding to each connector between two consecutive layers. Che et al. (2011) compared the performance of back propagation learning algorithm and genetic algorithm and found that back propagation learning algorithm is slightly superior to genetic algorithm for training neural network and yield better outcomes. By considering this, a multilayer feed-forward back propagation algorithm was adopted in this study to model LP. In this algorithm, flow of information is unidirectional which means that information moves only from input layer towards output layer through hidden layer. Each neuron is initially assigned a random weightage values. In this study, ANN-based lateral placement model is initialized with random weightage values which are subjected to Xavier distribution (Glorot and Bengio 2010). This distribution is commonly followed in weight initialization of neural networks and has the objective of keeping the variance of weightage values as constant at each layer. Variance of the weightage values (σ^2) was determined using the following formula.

$$(1) \quad \sigma^2(\text{weights}) = \frac{2}{(N_{\text{in}} + N_{\text{out}})}$$

N_{in} and N_{out} are the number of weights coming in and going out of the neuron respectively. Values provided at input nodes are multiplied with corresponding weightage values and thus the weighted sums are fed forward to the nodes of hidden layer. These weighted sums with added or subtracted biases (as given in Eqn. 2) are taken as input to the activation function of the neural network. These weighted sums with added or subtracted biases (as given in Eqn. 2) are taken as summing function which is taken as input to the activation function of the neural network.

$$(2) \quad O_i = f(\sum(w_i \times I_i) \pm \text{bias})$$

f is the activation function. O_i and I_i are the output and input signal corresponding to neuron 'i' respectively. The main purpose of using activation function at hidden layer is to convert the input signal into a meaningful output. Weighted sums of the functional values obtained at the hidden layer are fed forward to the output nodes. Output values are compared with the target values and the deviations which are referred as 'prediction errors', are computed. Based on this prediction error, the weightage values are again updated for the next iteration as exhibited in Fig. 1b. The training algorithm (feed forward back propagation) updates the weightage values and biases to map the arbitrary inputs correctly (Comert and Kocamaz 2017). This process is repeated until the average deviation in weightage values from the previous iteration comes under 5%. This was considered as the stopping criteria of iterations in the present study. Once this criterion is satisfied, the training process is stopped and the final output is obtained at the output nodes. The present study follows aforementioned methodology to develop a neural network model which can predict LP (metre) of a vehicle category if prevailing classified traffic volumes and directional split are given as inputs into the model.

Methodology for Estimation of Lane Indiscipline

Lane indiscipline in this study is conceptualized as the lateral shift of center of a vehicle across carriageway from the center of lane corresponding to the moving direction. LP of a vehicle predicted by ANN model developed in the previous phase was taken as input to estimate LI. The concept of LP and LI is exhibited in the Fig. 2.

Fig. 2. Concept of LP and LI

This study presents the following formula to determine lane indiscipline of a vehicle if lateral placement is known.

$$(3) \quad LI = LP - \frac{CW}{4}$$

CW is the carriageway width of the road in meter. Since, range of LP is $[0, CW]$, LI may vary theoretically within the range of $\left[\frac{-CW}{4}, \frac{3CW}{4}\right]$ and becomes zero when the center of a vehicle coincides with the center of lane. LI becomes positive when the center of vehicle is located at right side of the center of lane in the subject direction as shown in Fig. 2. Similarly, it becomes negative when the center of vehicle is located at left side of the center of lane in the subject direction. However, the above discussion and Eqn. 3 are only valid for two-lane undivided road. The generalized formula for multilane divided road is also presented in Eqn. 4.

$$(4) \quad LI = LP - \frac{(2m-1)CW}{2N}$$

N is total number of lane in each direction. m is the reference lane number which is accessed by the subject vehicle. m is an integer and may vary within the range of $[1, N]$. For the edge lane, $m = 1$ and for the median lane, $m = N$. For other middle lanes, m adopts values accordingly. A

general situation on two-lane undivided and four-lane divided road showing the ranges of lane indiscipline is shown in Fig. 3a and 3b respectively. When the center of the subject vehicle falls in the red zone, it refers to the negative lane indiscipline. Similarly, the center of vehicle falling in the green zone indicates the positive lane indiscipline. The dotted lines in Fig. 3 designate the zero lane indiscipline.

Fig. 3. A general situation showing positive and negative ranges for a) two-lane undivided carriageway, b) four-lane divided carriageway

A flow chart exhibiting the methodology followed in each phase of this study is given in Fig. 4.

Fig. 4. Flow chart exhibiting research methodology

However, prior to adopt this methodology for estimating LP and LI, it was required to collect field data which include traffic data (traffic volume, traffic composition, directional split and wheel positions of vehicle) and road geometric data (carriageway width and number of lanes).

Field Data Collection

The present study adopted videography survey as primary approach in order to collect traffic data while geometric details (like carriageway width) were manually measured. Videography survey was followed by data extraction process. Details of each phase along with the observed data are described in the following sub-sections.

Site Selection and Videography

A 30 m longitudinal stretch was chosen on Palam road, a collector urban road in New Delhi, the capital of India. Traffic data and road geometric details collected at this stretch were utilized to develop LP model and subsequently to estimate LI. However, in order to check the performance of the model developed, it was required to validate the model based on the field data collected at a different road stretch. To serve this purpose, another stretch was chosen on a collector urban road namely, Vigyan Path in Chandigarh, a metropolitan in northern India. Both of these roads are two-lane two-way undivided having a carriageway width of 9 m (4.5 m in each lane). Following criteria were considered while choosing these road stretches for the present study; a) the road section should be straight with no grade and located at least 300 m away from its nearby intersection; b) the section should be free from bus-stop, on-street parking, pedestrian movement and any other kind of potential side frictional activities; and c) the section must have a good pavement surface condition. In videography survey, a high resolution video camera was mounted on a 3.6 m tall camera-stand which was kept beside the road in such a way so that it can record the movement of traffic uninterruptedly on the selected longitudinal road stretch. Videography was carried out on a weekday in normal weather conditions for a duration of twelve hours (from 7 am to 7 pm) at Palam road and four hours (from 7 am to 11 am) at Vigyan path.

Data Extraction

After videography survey, video files were taken to laboratory and played on a computer screen to extract classified traffic volumes and lateral placement data. Based on observation, vehicles were classified into five categories; a) car; b) motorized two wheeler (2w); c) motorized three wheeler (3w); d) heavy vehicle (hv) and e) bicycle (bi). Bikes and scooters were included in '2w' category while '3w' includes only auto-rickshaw. 'hv' category considers buses and trucks. Classified traffic volumes were measured by counting the number of vehicles under each

category crossing the road section within 5-minutes time intervals. To extract lateral placement accurately from the video files, it was required to precisely locate the wheel positions of vehicles. Therefore, a number of virtual grid lines were drawn in such a manner so that the carriageway width could be divided into ten segments having equal width of 0.9 m. The segments were numbered from 1 to 10 in the subject direction starting from left to right edge of the carriageway as shown in Fig. 5.

Fig. 5. Study section with virtual grid lines

Whenever a vehicle belonged to car or hv category was crossing the section, the segment numbers corresponding to the position of left and right wheel of the front axle were noted. On the other hand, in case of 2w, 3w and bi, the position (in term of the segment number) of the only front wheel was noted. Center of each segment number defines a specific lateral position from the left edge of carriageway in the subject direction as given in Table 1.

Table 1. Lateral position of wheel corresponding to different segment number for 9 m wide carriageway

Lateral position, LPos (in meter) of a wheel can also be determined for any carriageway width based on a given segment number using Eqn. 5

$$(5) \quad LPos = \frac{(i_s - 0.5) \times CW}{N_s}$$

Where, ' i_s ' is the segment number corresponding to the subject wheel. CW is the carriageway width of road in meter and N_s is the total number of segments used to divide the carriageway width. Lateral placement of a car or hv was taken as the average of lateral positions

corresponding to its left and right wheel. However, in case of other vehicles i.e. 2w, 3w and bi, the lateral placement was taken as the lateral position of its front wheel.

In data extraction process, there were few occasions when the positions of wheel were getting blocked by the body of the subject and neighboring vehicles. To address this problem, following steps were taken carefully.

Step 1: Wheel positions of vehicles were primarily observed at the virtual transverse line near to the camera for closer inspection. The positions of only front wheels were recorded to measure the lateral placement of those vehicles which were coming towards the camera. Conversely, for vehicles moving away from camera, positions of rear wheels were recorded. In this way, the chances of blocking the view of wheels by its own body were completely avoided.

Step 2: Although the previous step eluded the chances of getting blocked by the body of the subject vehicle, there were approximately 3.5% cases where the wheel positions were blocked by its neighboring vehicles at the reference line. In such situations, the video was played forward or backward and taken to a frame where the wheel positions were clearly visible on the trap length selected for this study. There was not a single occasion when wheel positions of a vehicle were thoroughly blocked by other vehicles throughout the entire duration spent on a 30 m long road segment.

Observed Data

A wide variation in traffic volume, from 512 veh/h to 3708 veh/h, was observed at Palam road as traffic data covers both peak and off-peak hours. Also, traffic composition was observed varying with time. Cars and motorized two wheelers were present in major proportions as their combined

presence accounts for nearly 80% of the vehicular traffic. Details of traffic volume and its composition extracted from video files are given in Table 2.

Table 2. Ranges of collected traffic volume and the traffic composition

Extracted data of LP showed distinct ranges for different vehicle categories. Few popular statistical distribution were attempted to fit the dataset however, normal distribution was found as the best-fitted to represent LP for individual vehicle category. Results of Kolmogorov-Smirnov (K-S) and Anderson Darling (A-D) tests (as given in Table 3) ensured the goodness-of-fit of these representations as the observed statistic does not exceed its critical value for all motorized vehicle categories. Bicycles, the only non-motorized vehicle category considered, have unique characteristics from lateral placement perspective. Bicycle as a vehicle category always prefers to move near the edge of the road. Therefore, the observed statistic for bicycles exceeds its critical value and it implies that the lateral placement of bicycle is not following normal distribution.

Table 3. Distribution parameters and results of goodness-of-fit

Mean in Table 3, shows the average lateral placement whereas standard deviation indicates the consistency of a vehicle category in choosing lateral placement. Fig. 6 shows the distributions of LP and LI for individual vehicle categories across carriageway width.

Fig. 6. Distribution of LP and LI for different vehicle categories

Among motorized vehicles, two wheelers have the lowest mean (1.95 m) of LP. Overall they prefer to move at a lateral placement which is little left from the center of lane in the subject direction resulting in negative LI for two wheelers. On the other hand, a high mean value (3.05

m) of LP indicates that cars prefer to shift towards the center of road resulting in positive LI. However, three wheeler as a vehicle category was found to be the most accurate in placing themselves at a lateral position (2.22 m) close to the center of lane (2.25 m). From consistency aspect, heavy vehicles registered the minimum standard deviation (0.72 m) which makes them the most consistent among all motorized vehicle categories in choosing lateral position. On the other hand, two wheelers with the maximum standard deviation of 0.99 m are the most inconsistent in choosing lateral position. It is owing to the fact that motorized two wheelers being small sized and highly maneuverable, can pick any lateral position left empty by other surrounding vehicles. Moreover, it is to be mentioned here that LP of bicycles holds some unique characteristics as compared to other motorized vehicles. In absence of a separate bicycle lane, bicycles are enforced to share space with other fast-moving vehicles. Therefore, to ensure a safe distance from those vehicles, majority of bicyclists prefer to move at a lateral position near to the edge of road resulting in the lowest mean (0.53 m) and standard deviation (0.45 m). Observed data showed a wide range of LP for most of the vehicle categories; [0.90, 7.65] for car, [0.45, 7.65] for 2w, [0.90, 6.75] for 3w, [0.90, 7.65] for hv and [0.45, 2.25] for bi. The reason behind this variation of LP is the change in traffic conditions with time. Therefore, it is required to develop a lateral placement model which will be useful to predict the lateral placement of a vehicle category based on a given traffic conditions.

Estimation of Lateral Placement and Lane Indiscipline

Traffic data and road geometric details collected at Palam road were used to model LP and estimate LI. Methodology given in Section 2.1 was followed to develop an ANN-based lateral

placement model. The present study used MATLAB software to develop ANN-based lateral placement model. Since number of vehicle categories observed in the field is five, a total of six design variables which are the classified volumes of five vehicle categories and the directional split, were taken at input layer of the neural network. Similarly, five output variables i.e. LP of five vehicle categories were considered as the output variables. Few studies (Kannan et al. 2017; Premalatha and Valan Arasu 2016; Kisi and Uncuoglu 2005) compare the various training algorithm in neural network and based on the least error, it was found that Levenberg-Marquardt was the best training algorithm. The present study adopts Levenberg-Marquardt as the training algorithm tan-sigmoid as the activation function and to construct a six-in-five-out neural network. Tan-sigmoid is a popular activation function adopted in many studies (Biswas et al. 2017b; Yonaba et al. 2010). Among 215 sets of data points corresponding to classified volumes, directional split and LP of individual vehicles, 70% were used to train the model, the rest 30% were kept aside for testing purpose. Time required to train the neural network was around 50 seconds. LP obtained by the ANN-based model was used in Eqn. 3 and LI was estimated. Carriageway width (CW) measured as 9 m and the number of lanes (N) as 2 were also taken as inputs in Eqn. 3. Hence using LP model coupled with Eqn. 3 proposed in this study can predict the LP as well as the LI of any amongst the five vehicle categories considered for a given set of classified volumes and directional split.

Before employing the model, there was a prior need for model validation where the accuracy of the model in predicting LP would be checked. Field data collected at another two-lane undivided urban road i.e. Vigyan Path were used for this purpose. Classified traffic volumes and directional split observed at Vigyan Path were taken as input in the model and therefore, the model yielded a set of lateral placement values for individual vehicles. Lateral placement

predicted by the model were then compared with the lateral placement observed at Vigyan Path. Validation plots shown in Fig. 7, exhibit a good neighborhood between the observed and the predicted LP and LI values for each vehicle category.

Fig. 7. Validation Plots of LP and LI for different vehicle categories

To quantify this neighborhood, two accuracy parameters i.e. Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) were used.

$$(6) \quad MAPE_j = \frac{100}{n} \sum_{i=1}^n \left| \frac{P_j^i - O_j^i}{O_j^i} \right|$$

$$(7) \quad RMSE_j = \sqrt{\frac{\sum_{i=1}^n (P_j^i - O_j^i)^2}{n}}$$

P_j^i and O_j^i are the predicted and the observed value of LP for vehicle category 'j' corresponding to observation 'i' respectively. n is the total number of observations. As may be seen in Table 4, MAPE and RMSE obtained for a vehicle category are less than 0.25 and 0.55 respectively which ensures a strong agreement between the observed and the predicted values of LP.

Table 4. Validation results based on different accuracy measures for different vehicle categories

Sensitivity Analysis on Lateral Placement and Lane Indiscipline

A sensitivity analysis was performed to assess the influences of traffic volume, traffic composition and directional split on LP and LI. Classified traffic volumes in the input layer of the model were varied in such a manner so that traffic volume and its composition can vary systematically within its observed ranges. Also, the model developed offers flexibility to vary

directional split within its observed range and subsequently, the change in LP or LI as output was recorded.

Effect of Traffic Volume

In order to examine the influence of only traffic volume, the other design variables i.e. traffic composition and directional split were kept constant at predefined values. Classified traffic volumes were changed in such a fashion so that it could make traffic volume to vary within the observed range of [500, 3500 veh/h] with an interval of 500 veh/h. These classified volumes data along with a predefined directional split were taken as input in the ANN-based model which yielded a set of LP and LI values. These values were again plotted against traffic volume for each vehicle category as shown in Fig. 8.

Fig. 8. Effect of Traffic Volume on LP and LI for different vehicle categories

For cars, increase in traffic volume on the road causes increase in LP and LI. Since cars possess high acceleration with respect to other vehicle categories, specifically heavy vehicles, three wheelers and bicycles, they have more overtaking capabilities to deal with the increased traffic volume conditions. Therefore, increase in traffic volume intensifies the overtaking frequencies for cars which results in the increase in LP value. However, exactly the opposite trend was observed for heavy vehicles. Being a category of limited acceleration characteristics, heavy vehicles are generally overtaken rather than they overtake other vehicles (except bicycles) specifically at high traffic volume conditions. As traffic volume increases, frequency and need of overtaking maneuvers of other vehicles increase accordingly. Heavy vehicles shift more towards the left edge of carriageway so that overtaking vehicles can get sufficient lateral space for overtaking maneuvers. Motorized two wheeler and three wheeler showed a unique behaviour in

terms of lateral placement with the change in traffic volume condition. When traffic volume increases up to a certain level (2000 veh/h), it intensifies overtaking frequencies for both two wheelers and three wheelers. For a constant directional split, if traffic volume increases on a two-lane two-way undivided road beyond a certain level, opposite directional traffic movement starts impeding the smooth overtaking maneuvers and therefore, rate of increase in overtaking frequency drops. Due to this, LP and LI increase significantly with the increase in traffic volume up to a certain level (2000 veh/h) beyond which, the rate of increase reduces for two wheelers, three wheelers and even for cars. Further, at a very high traffic volume condition (more than 3000 veh/h), two wheelers and three wheelers being small sized and highly maneuverable, start violating traffic rules by overtaking other vehicles (except bicycles) from left side of the road. Hence, LP and LI for these two categories, decrease with increase in traffic volume as may be seen in Fig. 8. Bicycles, the only non-motorized vehicle observed in this study, shift further towards the edge of carriageway to maintain a safe distance from other fast-moving motorized vehicles at an increased traffic volume condition. As a result, both LP and LI for bicycles decrease as traffic volume increases on the road.

Effect of Traffic Composition

To examine the influence of traffic composition on LP and LI, traffic composition was varied within the observed range (as given in Table 2) while traffic volume and directional split were kept constant at predefined values. Due to the limitation in graphical representation, proportions of maximum two vehicle categories were varied simultaneously at a time keeping proportions of other vehicles constant. Subsequently, LP and LI predicted by the ANN-based model were recorded and then plotted against the proportion of different vehicle categories as shown in Fig. 9.

Fig. 9. Effect of Traffic Composition on LP and LI of a) car, b) motorized two wheeler, c) three wheeler, d) heavy vehicle and e) bicycle

Increase in the heavy vehicle proportion in the traffic stream insists overtaking tendencies for all vehicle categories (except bicycle). Therefore, LP and LI of car, three wheeler and even heavy vehicle itself increase as heavy vehicle proportion increases in the traffic stream. However, at a high traffic volume condition, two wheelers prefer to violate traffic rule and overtake a large sized vehicle like heavy vehicle from left side of the road. As a result, LP and LI decrease for two wheeler with the increase in heavy vehicle proportion. Bicyclists on the other hand, shy away more towards the edge of the road to ensure safety from the increased number of heavy vehicles. Therefore, LP and LI decrease for bicycles. Further, it was observed that the increase in proportion of car has less significant impact on LP and LI as compared to the increase in heavy vehicle proportion.

Effect of Directional Split

To assess the influence of directional split, classified traffic volumes in ANN-based lateral placement model were kept constant at predefined values and directional split was varied within the observed range i.e. 0.2 to 0.8 (as given in Table 2). Outputs yielded by the model were plotted against directional split to understand the influence of directional split on LP and LI for each vehicle category as shown in Fig. 10.

Fig. 10. Effect of Directional Split on LP and LI for different vehicle categories

Based on the concept of directional split adopted in this study, increase in directional split for a constant traffic volume signifies the increase in traffic volume in the subject direction replacing traffic volume in opposite directional movement. Increase in traffic volume in the subject

direction increases the demand of more lateral spaces for vehicles travelling towards the same direction. Accordingly, these vehicles shift more towards the adjacent lane which increases LP and LI of these vehicles. As may be seen in Fig. 10, LP and LI have positive correlations with directional split for all motorized vehicles although rate of increase in LP or LI is governed by the category of subject vehicle. For example, overall rate of increase for heavy vehicles is much lower as compared to other motorized vehicles. On the other hand, bicycles which generally move near the edge of carriageway, remain unaffected with the change in directional split.

Conclusions

This paper suggests a framework to estimate lateral placement and lane indiscipline of vehicles in a mixed traffic situation. The framework which consists of an ANN-based lateral placement model coupled with a formula of lane indiscipline quantification, will be useful to predict lateral placement and lane indiscipline of individual vehicle for any given traffic condition on two-lane two-way undivided urban road. The major findings of the study are given below.

- A wide variation in lateral placement was observed for different vehicle categories. Lateral placement varies within the boundaries of 0.90–7.65 m for cars, 0.45–7.65 m for two wheelers, 0.90–6.75 m for three wheelers, 0.90–7.65 m for heavy vehicles and 0.45–2.25 m for bicycles. The range of lateral placement for cars is 6.75 m i.e. 4.69 times of the average width of the vehicle (1.44 m). Similarly, the range of lateral placement for two-wheelers, three wheelers, heavy vehicles and bicycles are respectively 7.20 m, 5.85 m, 6.75 m and 1.80 m which correspond to 11.25, 4.18, 2.87 and 4 times of the average width of the respective vehicles. The study identifies the

change in traffic volume, traffic composition and directional split as the reason behind this variation of lateral placement.

- Lateral placement of vehicle follows normal distribution. However, the pattern of distribution changes subject to vehicle category. Cars in general, have the highest mean lateral placement however, heavy vehicle as a category is the most consistent among motorized vehicles in choosing lateral placement across the carriageway under varying traffic conditions. Being small sized and highly maneuverable, two wheelers have the flexibility to place them in any available lateral gap resulting in high dispersion of lateral placement and lane indiscipline.
- To assess the performance of the model developed, lateral placements and lane indisciplines predicted by the model were compared with the observed data on a separate road section having identical road geometry. Validation results showed that there is a good agreement between the lateral placement predicted by the model developed and the observed values.
- A significant influence of traffic volume was observed on lateral placement and lane indiscipline. However, the intensity and the trend of this influence varies with the category of subject vehicle. As traffic volume increases, lateral placement and lane indiscipline of cars increase. However, exactly the opposite trend was found in case of heavy vehicles. For motorized two wheelers and three wheelers, lateral placement and lane indiscipline increase when traffic volume increases up to a certain extent, beyond which, it decreases.
- Increase in proportion of heavy vehicles in the traffic stream instigates more overtaking tendencies for all motorized vehicles. As a result, lateral placement and lane

indiscipline increase for cars, three wheelers and heavy vehicles. However, with this increased heavy vehicle proportion, motorized two wheelers were observed violating the traffic rules as they start overtaking vehicles from the left side. Therefore, lateral placement and lane indiscipline for motorized two wheelers decrease with the increase in heavy vehicle proportion in the traffic mix. Change in proportion of cars has less significant impact on lateral placement and lane indiscipline of different vehicle categories as compared to the impact caused by changing heavy vehicle proportion.

- A very consistent impact on different vehicle categories was observed when directional split increases in the traffic stream. For constant traffic volume and its composition, lateral placement and lane indiscipline increase with the increase in directional split. Of course, the rate of increase differs corresponding to the category of subject vehicle.
- Bicycles, the only non-motorized vehicle category observed at the study location, have unique characteristics of lateral placement. Generally, bicycles prefer to move closer to the edge of carriageway resulting in a low average lateral placement (0.53 m). Also, lateral placement and lane indiscipline of bicycles do not get influenced significantly with the change in either traffic volume or directional split in the traffic stream. However, the increase in proportion of heavy vehicles (like trucks and buses) makes bicyclists feel unsafe and they shift more towards the edge of carriageway resulting in decrease of lateral placement and lane indiscipline.
- The graphs developed after sensitivity analysis will be useful for prediction of lateral placement and lane indiscipline of a vehicle type for a given traffic condition. However, the use of these graphs is strictly restricted to two-lane two-way undivided urban road. The methodology proposed in this study can be further used to develop similar models

and graphs for other types of road also. As future scope, the work can be extended to examine the influence of road geometric factors like carriageway width, shoulder width, horizontal curvature etc. on lateral placement and lane indiscipline.

- This study did not emphasize on the inter-vehicular lateral distance within a traffic stream. The inter-vehicular lateral distance holds significance specifically, in a mixed traffic scenario of a developing country. Although the information is useful in traffic simulation and safety assessment, in-depth research on this is yet to be conducted in the context of urban mixed traffic. This aspect can be taken up in future research.

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List of Symbols

The following symbols are used in this paper:

σ^2 = variance of the weightage values;

$2w$ = two wheeler;

$3w$ = three wheeler;

bi = bicycle;

CW = carriageway width of the road;

f = transfer function at hidden layer;

I_i = input signal corresponding to neuron ‘i’;

i_s = the segment number corresponding to the subject wheel;

LI = lane indiscipline of a vehicle;

LP = lateral placement of a vehicle;

LP_{os} = lateral position of a wheel;

m = reference lane number

n = total number of observations;

N = number of lanes on the carriageway;

N_{in} = number of weights coming in the neuron;

N_{out} = number of weights going out of the neuron;

N_S = total number of segments used to divide the carriageway width;

O_i = output signal corresponding to neuron 'i';

O_j^i = observed value of lateral placement for vehicle category 'j' corresponding to observation 'i';

P_j^i = predicted value of lateral placement for vehicle category 'j' corresponding to observation 'i';

w_i = weightage value corresponding to each connector between two consecutive layers.

Figure Captions

Fig. 1. a) Basic structure and b) iteration process to update weightage values of neural network

Fig. 2. Concept of LP and LI

Fig. 3. A general situation showing positive and negative ranges for a) two-lane undivided carriageway, b) four-lane divided carriageway

Fig. 4. Flow chart exhibiting research methodology

Fig. 5. Study section with virtual grid lines

Fig. 6. Distribution of LP and LI for different vehicle categories

Fig. 7. Validation Plots of LP and LI for different vehicle categories

Fig. 8. Effect of Traffic Volume on LP and LI for different vehicle categories

Fig. 9. Effect of Traffic Composition on LP and LI of a) car, b) motorized two wheeler, c) three wheeler, d) heavy vehicle and e) bicycle

Fig. 10. Effect of Directional Split on LP and LI for different vehicle categories

Table 1. Lateral position of wheel corresponding to different segment number for 9 m wide carriageway

Segment	1	2	3	4	5	6	7	8	9	10
No.										
Lateral	0.45	1.35	2.25	3.15	4.05	4.95	5.85	6.75	7.65	8.55
Position										
(m)										

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Table 2. Ranges of collected traffic volume and the traffic composition

	Volume (veh/h)	Directional Split	Traffic Composition					Total (%)
			% car	% 2w	% 3w	% hv	% bi	
Mean	2477	0.50	45.31	38.06	4.65	3.70	8.28	100
Minimum	512	0.19	21.88	23.61	0.00	0.00	0.00	-
Maximum	3708	0.81	64.58	48.39	10.06	15.23	17.19	-

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Table 3. Distribution parameters and results of goodness-of-fit

Parameters of Normal Distribution			Goodness-of-fit results				
Vehicle Type	Mean (meter)	Standard Deviation (meter)	Kolmogorov-Smirnov		Anderson Darling		Remarks
			Statistic		Statistic		
			Observed	Critical	Observed	Critical	
			Statistic	Value	Statistic	Value	
Car	3.05	0.91	0.09	0.10	1.95	3.87	Accept
2w	1.95	0.99	0.04	0.10	0.82	3.87	Accept
3w	2.22	0.81	0.07	0.10	1.03	3.87	Accept
hv	2.83	0.72	0.10	0.11	1.73	3.87	Accept
bi	0.53	0.45	0.31	0.11	4.84	3.87	Reject

Table 4. Validation results based on different accuracy measures for different vehicle categories

Sr.No.	Type of vehicle	MAPE	RMSE
1	Car	0.08	0.28
2	2w	0.12	0.25
3	3w	0.20	0.51
4	hv	0.14	0.49
5	bi	0.15	0.09

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