Acceleration Models for Two-Wheelers and Cars in Mixed Traffic: Effect of Unique Vehicle Following Interactions and Driving Regimes

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Abstract

Driving behaviour in mixed traffic condition is characterised by vehicle heterogeneity and lane-less movement. In such traffic conditions, the following response of a vehicle may be discontinuous and gets triggered when certain thresholds on relative speed and spacing with leaders are crossed. In this context, the present study segments the vehicular response into driving regimes using vehicle trajectory data based on relative speed and position. Acceleration models are formulated by featuring driving regimes and their interactions with mixed traffic attributes. These models are used to investigate the differences in the following behaviour of two-wheelers and cars. The proposed models capture the asymmetric behaviour and accounts for differences across driving regimes resulting in significantly better fit and realistic representation of mixed traffic.

Keywords: Mixed traffic attributes, Acceleration models, Driving regimes, Local area concentration, Vehicle trajectory extraction

Introduction

Driving behaviour of vehicles under mixed traffic environment involves complex interactions due to vehicle heterogeneity and weak lane discipline. There are wide variations in static and dynamic characteristics of vehicles that share the same road space, leading to multifaceted manoeuvres. On many urban roads in Indian cities, motorized two-wheelers (TW) and passenger cars constitute the major share of vehicle composition. The driving behaviour and vehicle characteristics of both these vehicle types are noticeably different from each other, which warrants careful investigation. In this context, the paper examines the dissimilarities and interactions between two-wheelers and cars by developing longitudinal acceleration models with specific focus on asymmetric behaviours across driving regimes. Driving regimes are the collection of actions by the subject vehicle resulting from imperfect perception and discontinuous response based on thresholds on stimulus like visual angle, speed, and spacing[1-4]. These driving regimes can influence the decision-making process of the subject vehicle. This study analyses the sensitivity of car and TW in mixed traffic to different driving regimes by developing new acceleration models based on vehicle trajectory data.

Previous studies have calibrated Wiedemann's driving behaviour model parameters from field data for different traffic facilities[2], vehicle types[3,4], and leader-follower combinations[5] for homogeneous traffic conditions. A few studies have also been carried out for calibrating these parameters for multiple vehicle types in heterogeneous traffic conditions[6]. But, acceleration models for mixed traffic condition from vehicle trajectory data, considering the effect of driving regimes along with mixed traffic attributes like leader-follower interactions, surrounding vehicle concentration and staggered following are yet to receive adequate research attention. The longitudinal response of subject vehicle under different driving regimes and the variations in the sensitivity of subject vehicle to relative speed and gap under each regime have not been examined for mixed traffic condition.

To address these gaps, the following objectives are pursued in this study:

1. To develop a longitudinal response model of a subject vehicle by modelling its acceleration using trajectory data with due consideration to driving regimes.

2. To investigate the role of mixed traffic attributes like leader-follower interactions, surrounding vehicle concentration and staggered following on the time-varying longitudinal response of subject vehicle using the above model.

3. To examine and quantify the differences in driving behaviour between cars and two-wheelers

Literature Review

Microscopic modelling deals with capturing the actions and reactions of vehicles under different situations including car-following, lane changing and gap acceptance[7-18]. Car-following models describe the acceleration characteristics of the following vehicle in response to the actions of its leader[19]. Several theories have been proposed to model car-following behaviours. These can be divided into five classes, based on behavioural assumptions, namely, stimulus-response models, safety distance/ collision avoidance models, action point / psycho-physical models, optimal velocity models and cellular-automata model[20]. These models have been developed for homogeneous lane-based conditions. Their applicability and transferability to mixed traffic conditions, however, have been questioned in the literature[21].

Within microscopic modelling scheme, the psycho-physical models aim to provide a more realistic representation of driving behaviour by allowing for imperfect perception and discontinuous response, based on thresholds on the visual angle, which in turn are influenced by relative speed and spacing. In this line of work, Michaels[22] defined the presumption of a driver to identify the approaching or receding leader depending upon the changes in the apparent size of the vehicle. Lee[23] gave thresholds for the perception of visual angle and found that drivers are unable to distinguish small changes in visual angles, and the response happens intermittently whenever visual angle thresholds are crossed. Two sets of models that explain the following state of a vehicle in response to the relative speed and spacing with the leader are Wiedemann 74 model for urban roads and Wiedemann 99 model for freeways[24]. Numerous studies attempted to calibrate these parameters from field data according to the traffic facilities (such as freeways, highways, intersections) and depending on vehicle types[2–5].

The calibration of car-following models is done to match the macroscopic parameters like stream speed, travel time, delay, and capacity. It is found that multiple types of interactions at microscopic level can arrive at same traffic flow parameters at macroscopic levels[25]. Zheng *et al.*[26] used NGSIM trajectory data to build vehicle type-dependent car-following models using visual imaging model (VIM). He *et al.*[27] put forward non-parametric car-following models, which could reproduce the trajectory of vehicles and traffic parameters from NGSIM data. Fan *et al*.[28] studied the impact of driving memory on car-following theory and found that the historical driving memory results in different types of regimes and manoeuvres. But these studies have seldom considered the development of acceleration models incorporating driving regimes and its interaction with relative speed and gap from vehicle trajectory data.

Among mixed traffic modelling methods, Gunay[29] modified the Gipps car-following equation to incorporate non-lane-based following by incorporating off-centred following of vehicles. Measures like traffic concentration and area occupancy have also been used to model the heterogeneous traffic conditions with no lane discipline[30]. Kanagaraj *et al.*[31] studied the influence of composition, intra-class variability, and lack of lane discipline on traffic flow characteristics in mixed traffic with significant motorized two-wheeler volumes. Ravishankar and Mathew[32] developed a model that incorporates vehicle-type dependent behaviour by modifying the Gipps model. Metkari *et al.*[33] modified this model by incorporating the off-centred car-following state proposed by Gunay[29]. In mixed traffic environment, the availability of trajectory data for various traffic facilities are limited. Because of the limited data and difficulty in data extraction, only a few studies have attempted to model the complex vehicular interactions (like vehicle following, lane changing, overtaking and gap-acceptance) that exits in heterogeneous non-lane-based traffic[34-40]. Most of the acceleration models developed until now have considered the relative speed and spacing between the leader and follower as the explanatory variables. But these studies did not develop an acceleration model from trajectory data by holistically incorporating mixed traffic attributes like staggered following, surrounding vehicle and leader-follower interactions along with driving regimes. The dissimilarity in following behaviour of cars and two-wheelers has seldom been modelled and analysed in the previous studies.

Data Collection and Extraction

For this study, a methodology for extracting mixed traffic trajectory data is developed using Python's graphical user interface. The data was collected from a six-lane divided mid-block section on Mount Poonamalee Road, Chennai, India. The chosen mid-block stretch is 250 m long with a carriageway width of 10.5 m (in the direction of flow) as in Figure 1.

The trajectory data of 4720 vehicles were obtained during a 40-minute time period using videographic method. Each vehicle's longitudinal and lateral position were recorded at a frame resolution rate of 1 sec which provides a total of 91754 data points. The total vehicle kilometres tracked is 1180. From the vehicle positions, finite difference method was used to compute speeds and acceleration. The extracted data at the microscopic level can be used for classifying the vehicle at each time step into the subject and surrounding vehicles.

Definition of Terms and Exploratory Analysis

This study models the acceleration behaviour of vehicles with due consideration to driving regimes along with other mixed traffic attributes.

Leader-Follower Pair Identification

Every vehicle in the stretch is considered as a subject vehicle for the duration of its presence in the study stretch. The vehicles surrounding the subject vehicle is identified based on the influence area concept. Influence area is defined as the region of influence around the subject vehicle, where the surrounding vehicles are present, which can fundamentally influence the driving behaviour[21]. The vehicle within this influence area which is immediately ahead (nearest in terms of longitudinal gap) of the subject vehicle and laterally overlaps with it is considered as the leading vehicle.

Categorization of Driving Regimes

The response of a follower to the stimulus it receives from the leader may be discontinuous because of imperfect perceptions about relative speed and gaps. Only when the perceptions cross certain thresholds, do these stimuli become perceived, which trigger a conscious change in the acceleration. The discontinuity in driving response can be captured using different driving regimes. The driver switches from one regime to another as soon as he/she reaches a certain threshold that can be expressed as a function of the speed difference and space headway. The response of subject vehicle while following the leader can result in various driving regimes, namely, free driving, conscious reaction, unconscious reaction, and emergency braking, as shown in Figure 2.

The Wiedemann 99 model parameters (AX, ABX, SDX and SDV) were used as limiting factors to define the driving regimes of each leader-follower pair based on relative speed and spacing. The inequalities are formulated for different thresholds based on the driving behaviour parameters for Chennai roads[1] and are given in Table 1. These inequalities primarily divides the driving behaviour into four regimes (as given in Figure 2): (a) Free Driving (if, $Gap > SDX$), (b) Emergency Braking (if, $Gap < ABX$), (c) Conscious Reaction (if, $\{ABX \leq Gap \leq SDX\}$ and $\{|Relative\ Speed| > SDV\}$), and (d) Unconscious Reaction (if, $\{ABX \leq Gap \leq SDX\}$ and $\{|Relative\ Speed| < SDV\}$). The conscious response can lead to acceleration and deceleration regimes depending on the speed difference between the leader and the follower. Positive speed difference can lead to acceleration and negative speed difference leads to deceleration. Thus, driving regimes are categorised at every instance of time, and are used as categorical variables in estimating the acceleration of the subject vehicle.

Mixed Traffic Attributes Considered in the Study

Two key features of mixed traffic that are likely to influence the following behaviour include staggered following and the influence of surrounding vehicles. These effects are captured using two variables, namely, lateral offset and local area concentration (LAC). The off centeredness created between the leader and follower during staggered following manoeuvre is termed as the lateral offset. It is the centre-to-centre lateral separation between leader-follower pair[21]. LAC is a measure of local density of vehicles around the subject vehicle, which depends on the type and composition of surrounding vehicles in the influence area[21]. It is defined as the ratio of the sum of areas of surrounding vehicles to the total area of influence of the subject vehicle (as given in Equation 1).

$$LAC = \frac{\sum_{i=1}^{\mathrm{N}} n_i A_i}{T_A} \times 100 \tag{1}$$

where, LAC is the Local Area Concentration expressed in percentage, N is the total number of vehicles present in the vicinity of the subject vehicle in the influence area, n_i and A_i are the number and area of different vehicle classes i present in the influence area (i is the index for vehicle types), T_A is the total area of influence region surrounding the subject vehicle.

Variation in Regressors Across Driving Regimes and Leader-Follower Pairs

The variation in explanatory variables (longitudinal gap, relative speed, LAC, and lateral gap) across driving regimes and vehicle pair combinations are studied. The four possible lead-lag combinations between car and TW are: car-car, TW-TW, car-TW, and TW-car as shown in Figure 3a. It is found that there are considerable variations in explanatory variables across various lead-lag pairs as well as driving regimes, which are shown in Figures 3b through 3e. From Figure 3b, longitudinal gap is observed to be more for free driving regime and considerably smaller for emergency braking regime. The gap maintained is high for car and minimum for TW under emergency braking regime. The relative speed regressor (Figure 3c) varies with regimes. The mean of relative speed is minimum for deceleration regime and maximum for acceleration regime. The local area concentration (Figure 3d) is highest for emergency braking regime and lowest for free driving, which is logical. The lateral gap (Figure 3e) maintained between leader and follower is highest for car-car pair and minimum for TW-TW pair. Within each vehicle pair, the lateral gap maintained is highest for emergency braking regime.

Vehicle Composition

As given in Figure 4, the composition of TW is 71%, car is 24%, auto is 2%, LCV is 2% and HCV is 1%. Thus, two-wheeler and car pair made up 95% of the composition on this corridor. Due to small sample size of other vehicle types, the analysis in this paper is restricted to TW and car pairs.

Lateral Position Distribution Across Lanes

The distribution of the lateral positions of cars and TWs across the road width is displayed in Figures 5a and 5b, respectively. The distribution pattern reveals that the car is placed mostly on the right side of the road, specifically in the median lane and middle lane. This is due to the speed advantage offered by the median lane. Although two-wheelers are uniformly distributed across the width, they are concentrated more over the middle lane. This is because the middle lane offers better manoeuvrability to shift to neighbouring positions as it provides more freedom to shift left or right. When considering the median lane, the TWs move closer to the median, whereas cars generally stay away from the median.

Descriptive Statistics of Microscopic Traffic Parameters in Longitudinal Direction

The summary statistics of speed, acceleration, and deceleration of vehicles in the longitudinal direction are given in Figure 6. The *mean and* maximum speed *are highest* for two-wheeler (TW). From Figure 6b, acceleration capability is high for two-wheelers compared to cars. Longitudinal deceleration values in Figure 6c shows TW has the highest mean value for deceleration compared to cars. When comparing the traffic parameters in the longitudinal direction, two-wheelers have marginally higher values than cars which can be explained by the build and model of vehicle.

Descriptive Statistics of Microscopic Traffic Parameters in Lateral Direction

The key characteristics of mixed traffic are the presence of considerable lateral movement, and the field data provide evidence for this. Figure 7 shows the descriptive statistics of the lateral movements and *indicate*s substantial differences among vehicle types. The mean values of lateral speed and acceleration are almost comparable between car and TW. But when considering the maximum values, the lateral speed and acceleration of TW are nearly double than that of car. This shows that the TWs have a greater lateral shifting tendency compared to cars.

The exploratory analysis demonstrates significant variations in microscopic driving attributes between cars and two-wheelers, which make a compelling case to develop separate models of driving behaviour. Therefore, acceleration models are formulated for car and TW with all possible leader-follower combinations.

Formulation of Acceleration Model

Base Model

Different non-linear models were tested including log-log, power law, box-cox transformed, and linear models with non-linear transformation of variables as well as separate linear models for acceleration and deceleration conditions. It was found that the multiple linear regression model (linear model with linear variables) turns out to have better explanatory power and easier to interpret with better goodness of fit, than the more complex model structures. Therefore, the base model is the multiple linear regression equation with the longitudinal acceleration of the subject vehicle as the response variable. The independent variables include relative speed and gap between the leader and the follower. The model structure is given in Equation 2.

$$a_s(t + \tau) = \beta_0 + \beta_1 v_{rel}(t) + \beta_2 S_{long}(t) + \varepsilon \qquad (2)$$

where, $a_s(t + \tau)$ is the acceleration or deceleration response of subject vehicle s in the longitudinal direction at a time $(t + \tau)$, t is the given instant of time, τ is the reaction time of subject vehicle, v_{rel} is the relative speed between the leader (l) and the subject vehicle (s) at time t in m/s ($v_{rel}(t) = v_l(t) - v_s(t)$), $S_{long}(t)$ is the bumper to bumper gap between the leader and the subject vehicle in the longitudinal direction in metres at time t, β_x is the parameter associated with variable x, and ϵ is the error term that is assumed to be normally distributed.

Modified Acceleration Model: Effect of Driving Regimes and Mixed Traffic Attributes

The effect of driving regimes on the follower's response is incorporated in the model. Categorical variable is used to represent different regimes in modelling the acceleration of the subject vehicle, maintaining the acceleration regime as the base condition. Free driving regime is not included in the model, as the follower response is not constrained by the leader.

Along with driving regimes, the mixed traffic attributes like staggered following and surrounding vehicle influence are also integrated into the model through the terms lateral offset and LAC. The interaction effect of regimes with relative speed, gap and LAC are incorporated into the model to replicate the non-linear behaviour of longitudinal response and is given in Equation 3.

$$\begin{aligned} a_s(t + \tau) = \beta_0 &+ \beta_1 v_{rel}(t) + \beta_2 S_{long}(t) + \beta_3 S_{lat}(t) + \beta_4 LAC(t) + \beta_5 \delta_{GW} \\ &+ \beta_6 \delta_{EB} + \beta_7 \delta_{EB} v_{rel}(t) + \beta_8 \delta_{EB} S_{long}(t) + \beta_9 LAC(t)\delta_{EB} + \beta_{10}\delta_{Dec} \\ &+ \beta_{11}\delta_{Dec} v_{rel}(t) + \beta_{12}\delta_{Dec} S_{long}(t) + \beta_{13} LAC(t)\delta_{Dec} \\ &+ \beta_{14}\delta_{Fol} + \beta_{15}\delta_{Fol} v_{rel}(t) + \beta_{16}\delta_{Fol} S_{long}(t) + \beta_{17} LAC(t)\delta_{Fol} + \varepsilon \end{aligned} \quad (3)$$

where, $S_{lat}(t)$ is the lateral separation between the leader and the subject vehicle, $LAC(t)$ is the local area concentration, δ_{GW} is the indicator variable for gap widening/gap closing representing the positive or negative relative speed, δ_{EB}, δ_{Dec}, δ_{Fol} and δ_{Acc} are categorical variables representing the emergency braking, deceleration, following and acceleration regimes, respectively, β_x is the coefficient associated with variable x and ε is the error term that is assumed to be normally distributed. The findings from the above model are presented below.

Findings and Discussion

Effect of Leader-Follower Interactions

The influence of leader-follower pair interaction is analysed using Equation 2 by comparing the unsegmented (aggregate) and segmented (disaggregate) acceleration models for subject vehicles. The data is segmented into four interactions based on leader-follower pairs - TW-TW, car-car, car-TW, and TW-car. Empirical data is used to estimate the model parameters, and these are shown in Table 2. Chow's test[41] is performed to test whether there is a statistically significant difference in the following behaviour across the four segments[40]. The goodness-of-fit measure, R^2 increases significantly from the combined model to pairwise leader-follower models (by 3.5 to 5.2 times) and a decrease in mean absolute error (by a factor of 2) is observed. The Chow test results confirms that segmenting based on leader-follower pair outperforms a model that neglects these interactions at 1% significance level. For all these models, the dependent and independent variables are positively correlated, which is logical as the acceleration of subject vehicle increases with increasing relative speed and spacing.

The magnitudes of coefficients vary across the four segments showing dissimilarities in the following behaviour based on the type of leader-follower pair and the size difference. There is significant difference in the magnitude and sign of intercepts also. For car-car and TW-TW pair, the intercept is found to be insignificant showing the follower to maintain the same speed if the relative speed difference is zero for a given longitudinal spacing. But for the same condition, the sign of the intercept for car-TW pair (0.117) is positive and for TW-car pair (-0.089) is negative. This suggests that when a smaller vehicle follows a larger leader (as in car-TW), it will try to seek lateral gaps and thus avoid following behaviour. Instead, if a larger follower like car when follows a smaller leader like TW, car will try to decelerate and adjust its speed with the leader as the gap seeking tendency get restricted due to its larger size. The intercept of combined unsegmented model, however, is positive and different from the segmented model. Thus, the combined model fails to capture the behavioural differences between car and TW when following leaders of different sizes.

Comparing the coefficients of relative speed across leader-follower interactions, its sign is positive for all the cases, which is logically sound. This suggests an increase in longitudinal response of subject vehicle with increase in leader's speed compared to follower. The magnitude varies across interactions with highest value for car-TW pair (0.457). The lowest relative speed coefficient magnitude is for TW-car pair (0.196). The magnitude of relative speed coefficient for car-car pair (0.315) and TW-TW pair (0.295) lies between these two values. This suggest that for a given spacing and relative speed difference, the following vehicle will decelerate more when the leading vehicle is bigger in size, this is because of the increased confinement posed by larger leader. The combined model fails to capture these behavioural differences across segments.

The responsiveness of the dependent variable to the longitudinal gap also varies across different segments. Longitudinal gap is statistically significant only for car-TW (0.101), and car-car (0.006) pairs. When a car becomes the leader (for both car-car and car-TW pairs), the subject vehicle's response is affected by the gap, as its manoeuvrability is restricted by the larger width of the lead vehicle (than when the lead vehicle is TW). The above model shows that the following behaviour not only depends on the type of the subject vehicle, but also on the leader type.

The next section extends the above model to explicitly account for different driving regimes, staggered following and presence of surrounding vehicles.

Effect of Driving Regimes and Mixed Traffic Attributes on Longitudinal Response of Subject Vehicle

The interactions between car and TW are analysed using the regression model by considering the response of the subject vehicle under different driving regimes. The heterogeneity and lane-less movement of vehicles in mixed traffic are integrated into the model using variables like - leader-follower interactions, lateral offset, and local area concentration. The modified model is given in Equation 3 and the estimated parameters are shown in Table 3. The results from this model are considerably superior to the base model, both statistically and logically. Besides, the mean absolute error value has also considerably reduced due to the inclusion of non-lane-based variables and asymmetry in driving regimes.

A comparison of modified model (Equation 3, with driving regimes and mixed traffic attributes) and base model (Equation 2) is done to evaluate whether the addition of dependent variables could improve the model. An F-test[42] is performed to compare the restricted (base) model with the unrestricted (modified) model using Equation 4. The F-statistic formula[42] calculates how much of the variance in the dependent variable, the base model is not able to explain as compared to the modified model, which is expressed as a fraction of the unexplained variance from the modified model. The F-test implies that the modified model (with driving regimes and mixed traffic attributes) is superior to the base model at 5% significance level.

$$F_{statistic} = \frac{\left(\frac{RSS_{base} - RSS_{modified}}{k_{modified} - k_{base}}\right)}{\left(\frac{RSS_{modified}}{n - k_{modified}}\right)} \tag{4}$$

where, RSS_{base} and $RSS_{modified}$ are the residual sum of squares of base restricted and modified unrestricted models, respectively, k_{base} and $k_{modified}$ are the number of estimated parameters in the restricted and unrestricted models, respectively, and n is the total number of data samples.

Effect of Driving Regimes:

For the different vehicle pair combinations, the coefficients of relative speed are found to be realistic - the acceleration of subject vehicle increases as the relative speed increases and vice-versa. The longitudinal gap is statistically insignificant for acceleration and following regimes, but significant for emergency braking and deceleration regimes. Acceleration regime happens when leader is faster than the subject vehicle. During the following regime, the subject vehicle is supposed to be unconsciously switching between acceleration and deceleration with positive and negative relative speed with leader. In both these regimes, the longitudinal gap is found to be statistically insignificant, whereas it is significant for emergency braking and deceleration regimes. The coefficient is positive, which indicates the acceleration of subject vehicle with increasing longitudinal gap and deceleration with a shrinking longitudinal gap and is intuitive. Significant differences in the following behaviour are observed depending on the following and leading vehicle types and based on driving regimes.

The key difference across different leader-follower pairs lies in the correlation of the dependent variable to relative speed and gap. The coefficient of relative speed varies with leader-follower pair and with regimes. Considering conscious reaction regimes, the relative speed coefficient is highest for deceleration regime, followed by emergency braking and acceleration regime. The signs of relative speed coefficients for different vehicle pair combinations are meaningful (positively correlated with subject vehicle's response) for these three regimes. During deceleration regime, the subject vehicle is closing in with the leader with respect to the reduction in speed difference between the two (gap-narrowing). However, in emergency braking regime, the subject vehicle becomes more alert about the spacing and thereby it shows increased sensitiveness towards longitudinal gap when compared to deceleration regime. The coefficient of longitudinal gap of TW-TW pair for emergency braking regime (0.45) is 12.8 times that of deceleration regime (0.035). This suggest that, when TW follows another TW, the influence of longitudinal gap in deciding the acceleration is highest for emergency braking regime, followed by deceleration regime.

During deceleration regime, the coefficient of relative speed is more for car-car pair (0.44), followed by TW-car pair (0.392). The relative speed coefficient is minimum for TW-TW pair (0.35). But for emergency braking regime, the coefficient of relative speed is high for TW-TW pair (0.249), followed by car-car pair (0.199). In acceleration regime, for the car-TW pair (0.276), subject vehicle is most responsive to relative speed compared to other vehicle pairs. From this it can be inferred that for TW-TW pair, the subject vehicle becomes cautious during emergency braking regime to the relative speed and longitudinal gap with the leader, compared to other regimes. But for car-car pair, the alertness to relative speed with leader is high during deceleration regime. Thus, it can be concluded that in mixed traffic condition, the alertness of vehicle towards different regimes varies with vehicle pair combinations between the leader and the follower.

Effect of Local Area Concentration (LAC) and its Interaction with Driving Regimes:

In addition to the relative position and speed between leader-follower pairs, the surrounding vehicles can also influence the response parameter due to weak lane disciplined condition. This effect is captured through the parameter called local area concentration (LAC), which estimates the density of vehicles in the surrounding area of the subject vehicle. A higher value of LAC implies a more compact packing of vehicles in the neighbourhood. The responsiveness of subject vehicle towards LAC varies with driving regimes. During acceleration regime, LAC and subject vehicle response are positively correlated. This indicates that if the concentration of surrounding vehicles increases, the longitudinal response of the subject vehicle increases. Considering emergency braking regime, the LAC and longitudinal response are negatively correlated for subject vehicle car and positively correlated for TW. Interestingly, this variable affects the response of both cars and two-wheelers significantly, but in two different ways. Cars found to decelerate with higher values of LAC because of greater confinement in deceleration cases. During deceleration, the magnitude of response of both car and TW are negatively correlated with LAC and the responsiveness is high for TW-car pair followed by car-car pair. However, when the subject vehicle is TW, the coefficient of LAC is 6.2 to 19 times smaller compared to car under emergency braking regime. During following regime, LAC is negatively correlated with acceleration for TW-TW, car-car, and TW-car pairs, whereas it is positively correlated for car-TW pair. The coefficient is highest for TW-car pair. Thus, the influence of surrounding vehicle on subject vehicle varies based on leader-follower pair and with driving regimes.

Effect of Staggered Following Behaviour:

Because of size differences, and due to the lack of lane discipline, the following vehicle may not be exactly aligned with the leader in front. The lateral offset is included as an explanatory variable to account for the effect of staggered following between the leader and the follower. The Lateral offset is statistically significant for all vehicle pairs except TW-TW pair. This coefficient is high when a car is following a TW. This may be due to the unpredictable and frequent shifting manoeuvres of TW as a leader, which could make the following vehicle more cautious to the changes in lateral gap with TW.

The study shows evidence of gap seeking behaviour of TW and following behaviour of car. The responsiveness of both vehicles to different regime conditions also varies significantly. The concentration of surrounding vehicles results in reduction in speed for car, whereas TW still manages to increase its speed with increasing LAC. The lateral gap maintained with the leader becomes a decisive factor for longitudinal response when the leading vehicle is a TW. Thus, these findings prove that in mixed traffic, there exist strong and asymmetric interactions between two-wheelers and cars that vary with driving regimes.

Summary and Conclusions

This study is an attempt to develop longitudinal response model of vehicles in mixed traffic under various driving regimes for various leader-follower interactions between car and TW. The model incorporating these parameters is found to be superior to the base model both statistically and realistically and can serve as a building block towards a full-fledged micro-simulation model. In particular, longitudinal equations are developed for different pairs of leader-follower combinations. This will enable the computation of acceleration of different vehicle types when following different kinds of leaders based on gap, relative speed difference, driving regime, concentration of vehicles in its neighbourhood, etc.

The asymmetry in the driving environment in mixed traffic is captured using the driving regime variable. Strong and asymmetric interactions between two-wheelers and cars are observed in this study, which vary with driving regimes. It can also be concluded that in mixed traffic, the alertness of vehicle in different regimes varies with leader-follower pair based on their types and size differences. The present study provides evidence that the behaviours of car and TW are noticeably different. Considering the impact of lead vehicle, the alertness of subject vehicle is high when the leader is a car than when it is a TW. With respect to the following behaviour, the car adjusts its acceleration in accordance with the relative position and speed with the leader, whereas the TW is only sensitive to the relative speed. For all the regimes under consideration, the sensitivity of the response variable is more for a car than for a TW. Similarly, the responsiveness to relative speed and spacing is found to vary with the leading vehicle and is found to be high for a leading car than a two-wheeler. The influence of surrounding vehicle concentration varies depending on the regime as well as leading and following vehicle types. The effect of lateral offset parameter is also found to change with the leading and following vehicle characteristics.

It can be concluded that there exists asymmetric following behaviour across driving regimes, which furthermore varies with the leading and following vehicle types. This modelling scheme could reasonably segregate the performance of car and TW in a mixed traffic environment. In the present study, driving behaviour is captured with more realism through the consideration of regimes of driving, leader-follower interactions, and local area concentration. The use of trajectory data in deriving mixed traffic attributes and utilising it in driving behaviour modelling adds novelty to the state-of-art car following models for mixed traffic condition and can find potential application in micro-simulation. The developed equations will be helpful in the vehicle movement phase of micro-simulation by computing acceleration values, and further numerically integrating it to update the vehicle's speed and position. Such microsimulation models will help in more realistic evaluation of level-of-service (LoS), safety, and capacity. Thus, the models and findings from this research work can be useful towards developing simulation-based traffic management and operation strategies in future studies.

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Table 1. Inequalities Used for Segmenting the Data into Different Driving Regimes

Subj. Veh.	$SDV_{Closing}$	$SDV_{Opening}$	Condition for Regimes				
			Emerg. Braking	Free Driving	Acceleration	Deceleration	Following
Car	$\frac{\Delta x - 0.523}{6.79}$	$\frac{\Delta x - 0.460}{-7.60}$	$\Delta x \leq 4.8m$	$\Delta x > 10.0m$	$4.8m < \Delta x \leq 10.0m$		
					$\Delta v \leq SDV_{opening}$	$\Delta v \geq SDV_{closing}$	$SDV_{opening} < \Delta v < SDV_{closing}$
TW	$\frac{\Delta x - 0.0034}{6.77}$	$\frac{\Delta x + 0.00274}{-7.54}$	$\Delta x \leq 1.06m$	$\Delta x > 10.7m$	$1.06m < \Delta x \leq 10.7m$		
					$\Delta v \leq SDV_{opening}$	$\Delta v \geq SDV_{closing}$	$SDV_{opening} < \Delta v < SDV_{closing}$

- *Δx and ΔV represent relative position (spacing) and relative speed between the leader and follower, respectively.*
- *$SDV_{closing}$ and $SDV_{opening}$ are the maximum difference in velocity for following during closing and opening, respectively.*

Table 2. Comparison of Aggregate and Disaggregate Interaction Models

Leader-Follower Interaction Models	Sample Size	Coefficients			R^2	MAE
		b_0 *(Intercept)*	b_1 (v_{rel})	b_2 (S_{long})		
Aggregate Model	49899	0.053	0.244	0.003	0.078	1.606
TW-TW	21879	0.002*	0.295	0.005*	0.278	0.89
Car-Car	6755	0.003*	0.315	0.006	0.306	0.75
Car-TW	9344	0.117	0.457	0.101	0.320	0.75
TW-Car	6198	-0.089	0.196	0.009*	0.398	0.71

* represents intercept/variable not statistically significant at 5%.

Table 3a Modified Acceleration Model Coefficients

Leader-follower Interaction Models	Coefficients for																	
	b_0 *(Intercept)*	b_1 (v_{rel})	b_2 (S_{long})	b_3 (S_{lat})	b_4 (LAC)	b_5 (δ_{GW})	b_6 (δ_{EB})	b_7 $(\delta_{EB} * v_{rel})$	b_8 $(\delta_{EB} * S_{long})$	b_9 $(\delta_{EB} * LAC)$	b_{10} (δ_{Dec})	b_{11} $(\delta_{Dec} * v_{rel})$	b_{12} $(\delta_{Dec} * S_{long})$	b_{13} $(\delta_{Dec} * LAC)$	b_{14} (δ_{Fol})	b_{15} $(\delta_{Fol} * v_{rel})$	b_{16} $(\delta_{Fol} * S_{long})$	b_{17} $(\delta_{Fol} * LAC)$
TW-TW	-1.09*	0.15	0.00*	0.00*	0.005	1.98	0.24*	0.099	0.45	-0.01*	0.93	0.20	0.035	-0.01	0.67	-0.65	-0.02*	-0.01
Car-Car	-0.946	0.129	-0.002*	0.060	0.016	1.709	0.484	0.070	0.011*	-0.028	0.857	0.311	0.062	-0.047	0.586	-0.488	0.001*	-0.026
Car-TW	-1.086	0.276	-0.023*	0.110	0.010	1.923	0.305*	-0.227	0.317*	-0.006*	0.961	0.093	0.069	-0.012	0.610	-0.786	0.006*	0.000*
TW-Car	-1.273	0.100	0.022*	0.180	0.010*	1.836	0.533	-0.035*	-0.061	-0.015	0.700	0.292	0.081	-0.038	1.153	-0.477	-0.077	-0.017

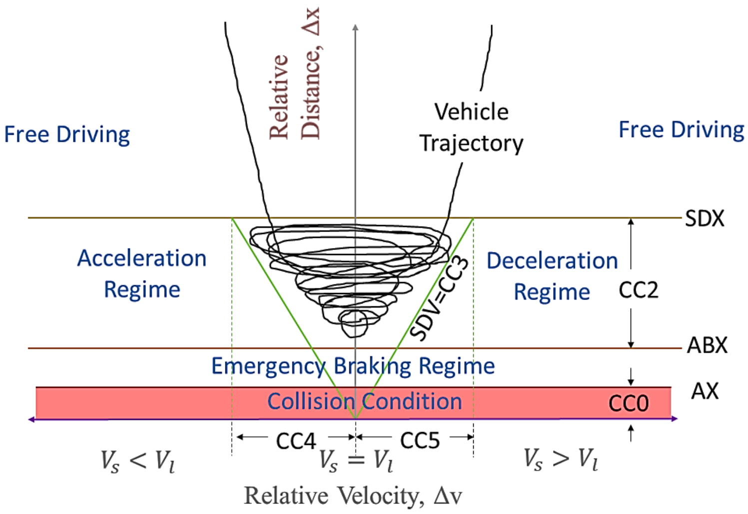
* *represents intercept/variable not statistically significant at 15%.*

Table 3b Goodness of Fit of Modified Acceleration Model

Leader-follower Interaction Models	Sample Size	R^2	MAE
TW-TW	10187	0.363	0.97
Car-Car	3504	0.423	0.84
Car-TW	4179	0.329	1.01
TW-Car	3067	0.446	0.79

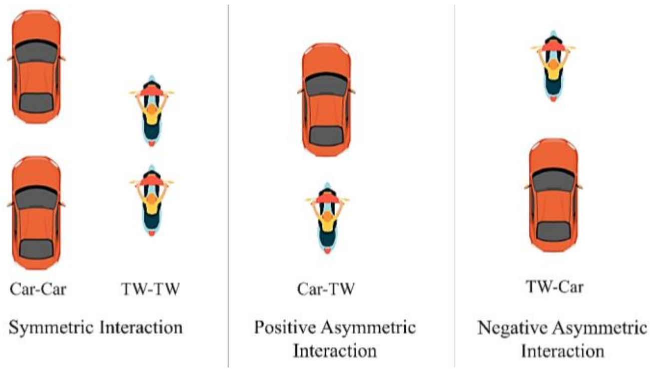
List of Figures

Figure 1. Screen Shot of Study Corridor with Gridlines Overlaid.

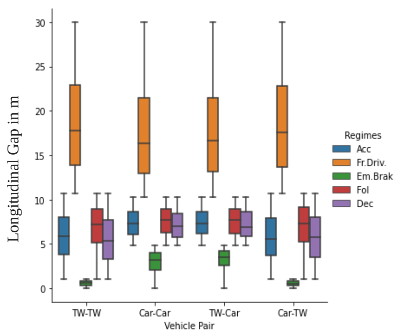


(CC0 to CC9: driving behaviour parameters; AX: minimum distance headway in standstill condition; ABX: minimum desired following distance to avoid a collision; SDV: maximum difference in velocity for following, SDX: maximum desired following distance[1])

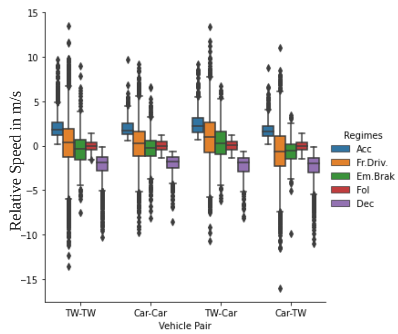
Figure 2. Figurative Representation of Wiedemann 99 Model Calibration Parameters



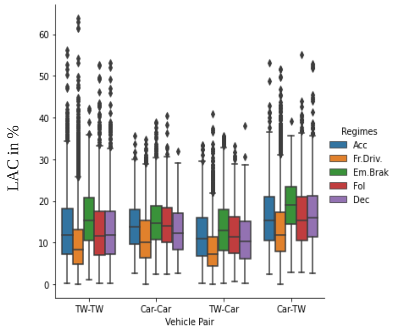
a) Leader-Follower Pair Combination



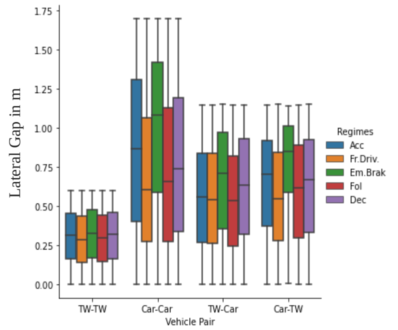
b) Longitudinal Gap



c) Relative Speed



d) LAC



e) Lateral Gap

Figure 3. Plots Showing the Variations in Independent Variables with Driving Regimes and Size Differential Interactions

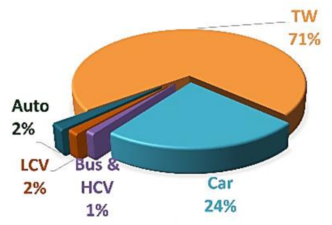


Figure 4. Vehicle Composition

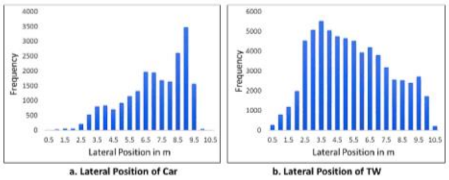


Figure 5. Lateral Placement Distribution of Car and TW

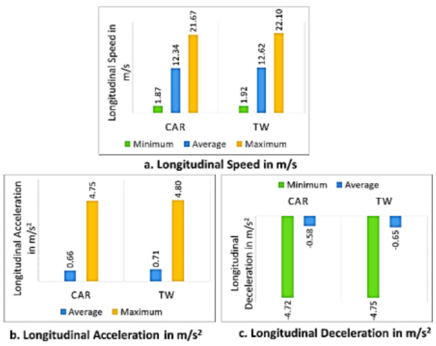


Figure 6. Disaggregate Vehicular Parameters in Longitudinal Direction

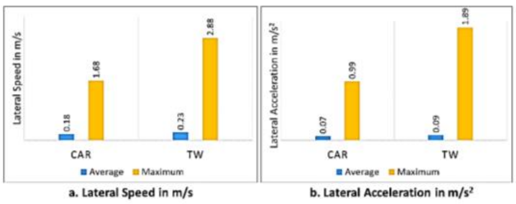


Figure 7. Vehicular Parameters in Lateral Direction