Acceleration models for two-wheelers and cars in mixed traffic: effect of unique vehicle-following interactions and driving regimes

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Driving behaviour in mixed traffic conditions is characterized 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 the leaders are crossed. In this context, the present study segments 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 study the differences in the following behaviour of two-wheelers and cars. The proposed models capture the asymmetric behaviour and account for differences across driving regimes, resulting in a significantly better fit and realistic representation of mixed traffic.

Keywords: Acceleration models, driving regimes, mixed traffic attributes, local area concentration, vehicle trajectory extraction.

DRIVING behaviour of vehicles under a 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 (TWs) 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 studies. In this context, the present study examines the dissimilarities and interactions between TWs and cars by developing longitudinal acceleration models with specifically focusing on asymmetric behaviours across driving regimes. Driving regimes are a collection of actions by the subject vehicle resulting from imperfect perception and discontinuous response based on the thresholds of stimuli 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 cars and TWs in mixed traffic to different driving regimes by developing 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]. However, acceleration models for mixed traffic conditions 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 a subject vehicle under different driving regimes and the variations in the sensitivity of the subject vehicle to relative speed and gap under each regime have not been examined for mixed traffic conditions.

To address these gaps, the following objectives are pursued in this study: (i) To develop a longitudinal response model of a subject vehicle by modelling its acceleration using trajectory data with due consideration to driving regimes. (ii) To examine the role of mixed traffic attributes like leader–follower interactions, surrounding vehicle concentration and staggered following on the time-varying longitudinal response of the subject vehicle using the above model. (iii) To examine and quantify the differences in driving behaviour between cars and TWs.

Literature review

Microscopic modelling captures 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 behaviour. These can be divided into five classes based on behavioural assumptions, namely stimulus-response models, safety distance/collision avoidance models, action

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point/psycho-physical models, optimal velocity models and cellular automata models[20]. These models have been developed for homogeneous lane-based conditions. Their applicability and transferability to mixed traffic condition, however, have been questioned in the literature[21].

Within the microscopic modelling scheme, the psychophysical 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 cannot distinguish small changes in visual angles, and the response occurs 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 the microscopic level can arrive at the 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 the visual imaging model (VIM). He *et al.*[27] developed 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. However, these studies have seldom considered the development of acceleration models incorporating driving regimes and their interaction with relative speed and gap from vehicle trajectory data.

Figure 1. Screen shot of the study corridor with gridlines overlaid.

Among mixed traffic modelling methods, Gunay[29] modified the Gipps car-following equation to incorporate a non-lane-based following by incorporating an off-centred following of vehicles. Measures like traffic concentration and area occupancy have also been used to model heterogeneous traffic conditions with no lane discipline[30]. Kanagaraj *et al.*[31] studied the influence of composition, intraclass variability and lack of lane discipline on traffic flow characteristics in mixed traffic with significant motorized TW 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 a mixed traffic environment, the availability of trajectory data for various traffic facilities is limited. Due to 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 exit 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 explanatory variables. However, 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 TWs has seldom been modelled and analysed in previous studies.

Data collection and extraction

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

The trajectory data of 4720 vehicles were obtained during a 40 min time period using videographic method. The longitudinal and lateral positions of each vehicle were recorded at a frame resolution rate of 1 sec, which provides a total of 91,754 data points. The total distance travelled by the vehicle was 1180 km. From the vehicle positions, finite difference method was used to compute speed 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.

Table 1. Inequalities used for segmenting the data into different driving regimes

Subject vehicle	$SDV_{closing}$	$SDV_{opening}$	Emergency braking	Free driving	Conditions for regimes: Acceleration	Deceleration	Following regime
						$4.8\ m < \Delta x \leq 10.0\ m$	
Car	$(\Delta x - 0.523)/6.79$	$(\Delta x - 0.460)/-7.60$	$\Delta x \leq 4.8\ m$	$\Delta x > 10.0\ m$	$\Delta \nu \leq SDV_{opening}$	$\Delta \nu \geq SDV_{closing}$	$SDV_{opening} < \Delta \nu < SDV_{closing}$
						$1.06\ m < \Delta x \leq 10.7\ m$	
Two-wheeler (TW)	$(\Delta x - 0.0034)/6.77$	$(\Delta x + 0.00274)/-7.54$	$\Delta x \leq 1.06\ m$	$\Delta x > 10.7\ m$	$\Delta \nu \leq SDV_{opening}$	$\Delta \nu \geq SDV_{closing}$	$SDV_{opening} < \Delta \nu < SDV_{closing}$

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.

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 are 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 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 triggers 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 the subject vehicle while following the leader can result in various driving regimes, namely free driving, conscious reaction, unconscious reaction and emergency braking (Figure 2).

The Wiedemann 99 model parameters (AX, Minimum distance headway in standstill condition; ABX, Minimum desired following distance to avoid collision; SDV, Maximum difference in velocity for following and SDX, Maximum desired following distance) were used as limiting factors to define the driving regimes of each leader–follower pair based on relative speed and spacing. The inequalities were formulated for different thresholds based on the driving behaviour parameters for Chennai roads (Table 1)[1]. These inequalities primarily divide 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 ≤ gap ≤ SDX} and {|Relative speed| > SDV}) and (d) unconscious reaction (if {ABX ≤ gap ≤ 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 to deceleration. Thus, driving regimes are categorized at every instance of time and used as categorical variables in estimating the acceleration of the subject vehicle.

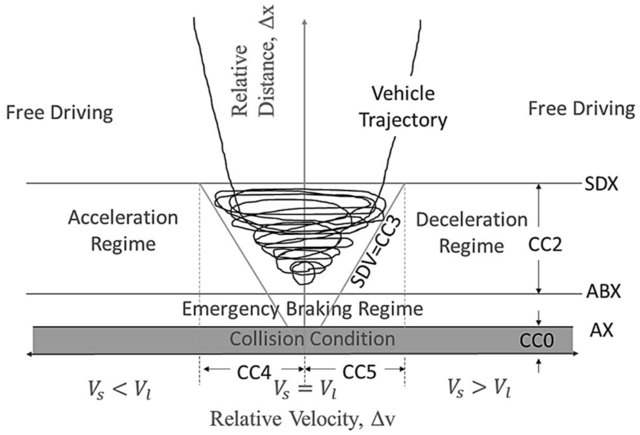

Figure 2. Figurative representation of Wiedemann 99 model calibration parameters. CC0 to CC9, Driving behaviour parameters; AX, Minimum distance headway in standstill condition; ABX, Minimum desired following distance to avoid collision; SDV, Maximum difference in velocity for following; SDX, Maximum desired following distance[1].

Mixed traffic attributes considered in the study

Two key features of mixed traffic that are likely to influence the following behaviour include staggered following

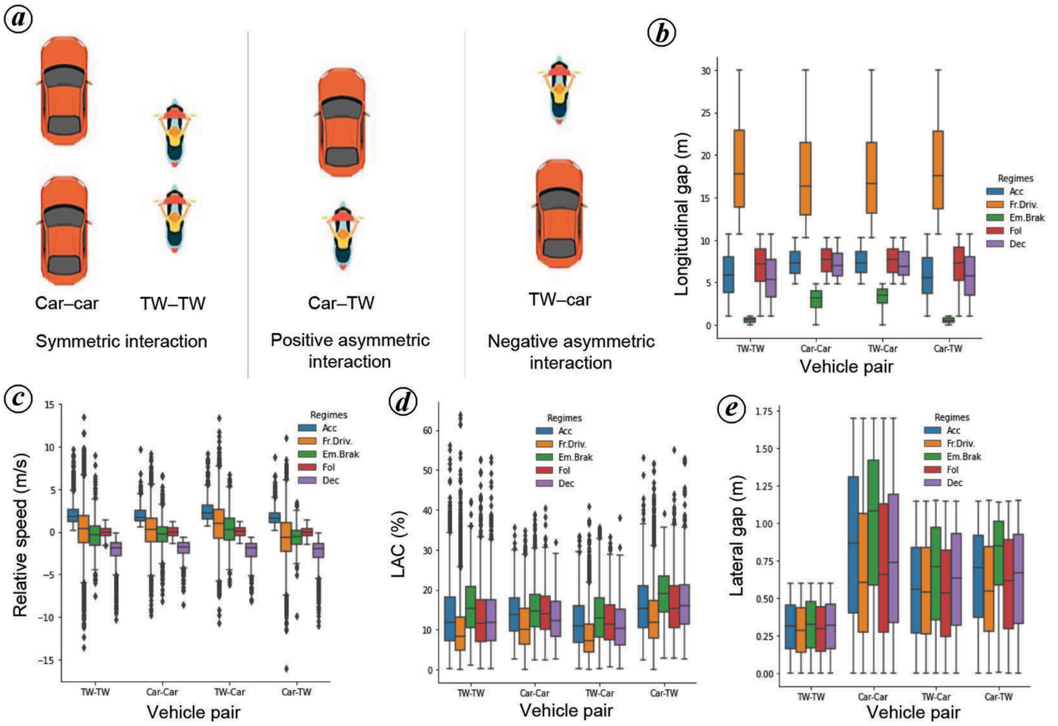

Figure 3. Plots showing variations in independent variables with driving regimes and size differential interactions. ***a***, Leader–follower pair combination; ***b***, Longitudinal gap; ***c***, Relative speed; ***d***, Local area concentration; ***e***, Lateral gap.

and influence of the surrounding vehicles. These effects are captured using two variables, namely lateral offset and local area concentration (LAC). The off-centredness created between the leader and follower during staggered following manoeuvre is known as the lateral offset. It is the centre-to-centre lateral separation between a 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 the surrounding vehicles in the influence area[21]. LAC is defined as the ratio of the sum of areas of surrounding vehicles to the total area of influence of the subject vehicle as in eq. (1).

$$\mathrm{LAC} = \frac{\sum_{i=1}^{N} n_i A_i}{T_A} \times 100, \qquad (1)$$

where LAC is the local area concentration expressed in percentage, N 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 respectively (i is the index for vehicle types) and T_{A} is the total area of the 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 was studied. The four possible lead–lag combinations between cars and TW are: car–car, TW–TW, car–TW and TW–car (Figure 3 *a*). There was considerable variation in the explanatory variables across various lead–lag pairs as well as driving regimes (Figure 3 *b*–*e*). From Figure 3 *b*, the longitudinal gap is observed to be more for free driving regime and considerably smaller for emergency braking regime. The gap maintained is high for cars and minimum for TWs under emergency braking regime. The relative speed regressor varied with regimes (Figure 3 *c*). The mean of relative speed was minimum for deceleration regime and maximum for acceleration regime. The local area concentration was highest for emergency braking regime and lowest for free driving, which is logical (Figure 3 *d*). The lateral gap maintained between the leader and follower was highest for the car–car pair and minimum for the TW–TW pair (Figure 3 *e*). For each vehicle pair, the lateral gap maintained was highest for the emergency braking regime.

Vehicle composition

As shown in Figure 4, the composition of TWs is 71%, cars 24%, autos 2%, light commercial vehicles (LCVs) 2% and heavy commercial vehicles (HCVs) 1%. Thus, the TW–car pair contributes to 95% of the composition on this corridor. Due to small sample size of other vehicle types, the analysis in this study restricted to TW–car pairs.

Lateral position distribution across lanes

The distribution of lateral positions of cars and TWs across the road width is displayed in Figure 5 *a* and *b* respectively. The distribution pattern reveals that cars are 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 TWs 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 to the 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

Figure 6 *a–c* provides the summary statistics of speed, acceleration and deceleration of vehicles in the longitudinal direction respectively. The mean and maximum speed are highest for TWs. Figure 6 *b* reveals that acceleration capability is high for TWs compared to cars. Longitudinal deceleration values in Figure 6 *c* shows that TWs have the highest mean value for deceleration compared to cars. When comparing the traffic parameters in the longitudinal direction, TWs have marginally higher values than cars, which can be explained by the build and model of the vehicles.

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 indicates substantial differences among vehicle types. The mean values of lateral speed and acceleration are almost comparable between cars and TWs. When considering the maximum values, the lateral speed and acceleration of TWs are nearly double those of cars. This shows that TWs have a greater lateral shifting tendency compared to cars.

The exploratory analysis demonstrates significant variations in microscopic driving attributes between cars and TWs, which make a compelling case to develop separate models of driving behaviour. Therefore, acceleration models have been formulated for cars and TWs with all possible leader–follower combinations.

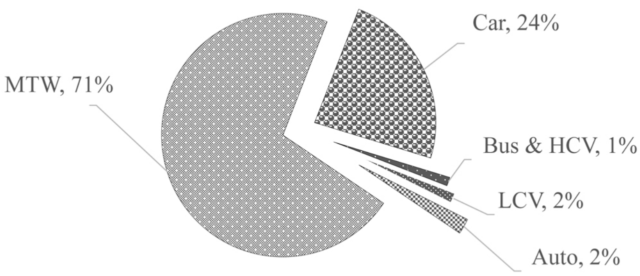

Figure 4. Vehicle composition. MTW, Motorized two-wheeler.

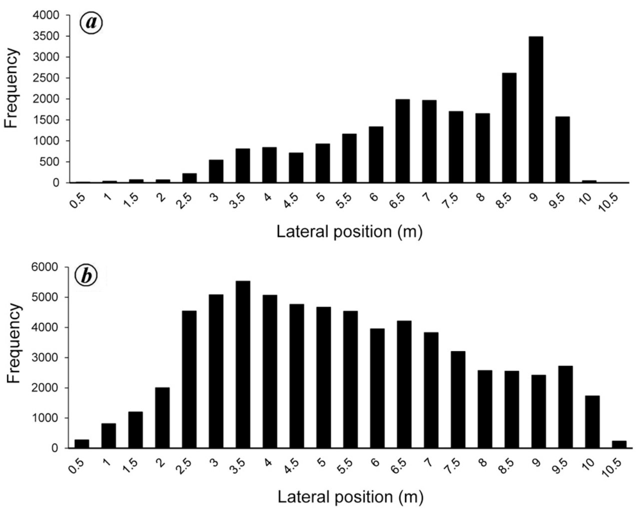

Figure 5. Lateral placement distribution of (***a***) cars and (***b***) two-wheelers (TWs).

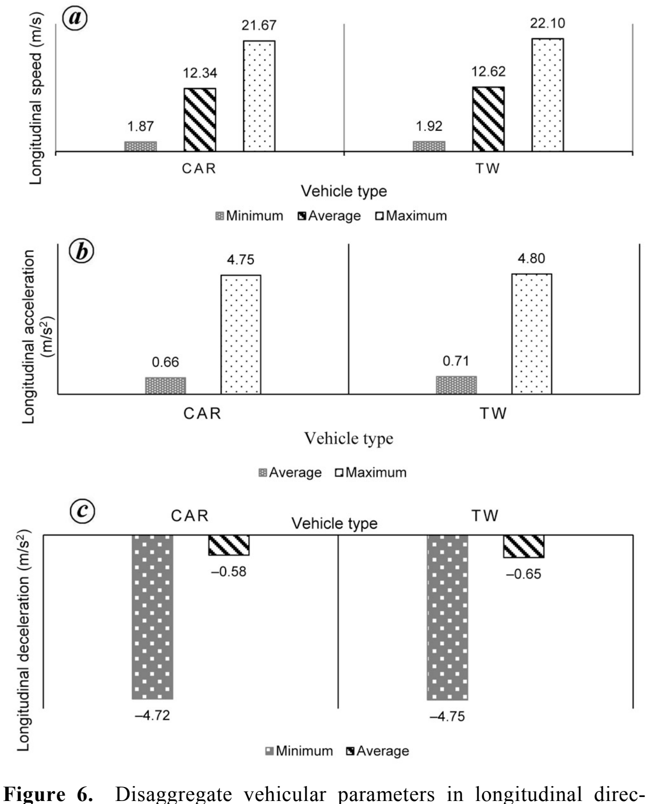

Figure 6. Disaggregate vehicular parameters in longitudinal direction. ***a***, Longitudinal speed (m/s); ***b***, Longitudinal acceleration (m/s^2); ***c***, Longitudinal deceleration (m/s^2).

Formulation of the acceleration model

Base model

Different nonlinear models were tested including log–log, power law, box–cox transformed, and linear models with nonlinear 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) had better explanatory power and was 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 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 eq. (2).

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

where $a_s(t+\tau)$ is the acceleration or deceleration response of the subject vehicle s in the longitudinal direction at a time $(t+\tau)$, t the given instant of time, τ the reaction time of the subject vehicle, v_{rel} (m/s) the relative speed between the leader (l) and the subject vehicle (s) at time t ($v_{rel}(t) = v_l(t) - v_s(t)$), $S_{long}(t)$ the bumper-to-bumper gap (m) between the leader and the subject vehicle in the longitudinal direction at time t, β_x 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 was incorporated in the model. Categorical variable was used to represent different regimes in modelling the acceleration of the subject vehicle, maintaining the acceleration regime as the base condition. Free driving regime was not included in the model, as the follower response was not constrained by the leader.

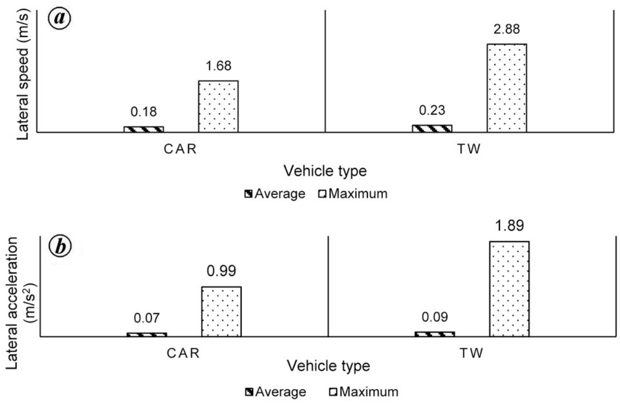

Figure 7. Vehicular parameters in lateral direction. ***a***, Lateral speed (m/s); ***b***, Lateral acceleration (m/s^2).

Along with driving regimes, the mixed traffic attributes like staggered following and surrounding vehicle influence were also integrated into the model through lateral offset and LAC. The interaction effect of regimes with relative speed, gap and LAC was incorporated into the model to replicate the nonlinear behaviour of longitudinal response, and is given in eq. (3).

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

where $S_{lat}(t)$ is the lateral separation between the leader and subject vehicle, LAC(t) the local area concentration, δ_{GW} the indicator variable for gap widening/gap closing representing positive or negative relative speed, δ_{EB}, δ_{Dec}, δ_{Fol} and δ_{Acc} are categorical variables representing emergency braking, deceleration, following and acceleration regimes respectively, β_x 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.

Results and discussion

Effect of leader–follower interactions

The influence of leader–follower pair interaction was analysed using eq. (2) by comparing the unsegmented (aggregate) and segmented (disaggregate) acceleration models for subject vehicles. Data were segmented into four interactions based on leader–follower pairs: TW–TW, car–car, car–TW and TW–car. Empirical data were used to estimate the model parameters. Table 2 shows these model parameters. Chow's test was performed to test whether there is a statistically significant difference in the following behaviour across the four segments[40,41]. The goodness-of-fit measure, R^2 increased significantly from the combined model to pairwise leader–follower models (by 3.5–5.2 times) and a decrease in the mean absolute error (by a factor of 2) was observed. The Chow test results confirm 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 the subject vehicle increases with increasing relative speed and spacing.

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	49,899	0.053	0.244	0.003	0.078	1.606
TW–TW	21,879	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 intercepts/variables not statistically significant at 5%. MAE, mean absolute error.

The magnitudes of coefficients varied across the four segments showing dissimilarities in the following behaviour based on the type of leader–follower pair and the size difference. There was significant difference in the magnitude and sign of the intercepts as well. For car–car and TW–TW pairs, the intercept was found to be insignificant showing the follower to maintain the same speed if the relative speed difference was zero for a given longitudinal spacing. However, for the same condition, the sign of the intercept for the car–TW pair was positive (0.117) and for the TW–car pair it was negative (–0.089). 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 a car follows a smaller leader like a TW, the 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, was positive and different from the segmented model. Thus, the combined model failed to capture the behavioural differences between cars and TWs when following leaders of different sizes.

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

The responsiveness of the dependent variable to the longitudinal gap also varied across different segments. Longitudinal gap was statistically significant only for the 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 response of the subject vehicle is affected by the gap, as its manoeuvrability is restricted by the larger width of the lead vehicle (than when the lead vehicle is a 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 the presence of surrounding vehicles.

Effect of driving regimes and mixed traffic attributes on longitudinal response of subject vehicle

The interactions between cars and TWs were 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 were integrated into the model using variables like leader–follower interactions, lateral offset and LAC. The modified model is represented by eq. (3) and Tables 3 and 4 show the estimated parameters. The results from this model were considerably superior to the base model, both statistically and logically. Besides, the mean absolute error value had also considerably reduced due to the inclusion of non-lane-based variables and asymmetry in the driving regimes.

A comparison of the modified model (eq. (3) with driving regimes and mixed traffic attributes) and the base model (eq. (2)) was done to evaluate whether the addition of dependent variables could improve the model. An *F* test[42] was performed to compare the restricted (base) model with the unrestricted (modified) model using eq. (4)[42]. The *F*-statistics calculates how much of the variance in the dependent variable the base model is unable to explain compared to the modified model, which is expressed as a fraction of the unexplained variance from the modified model[42]. 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.

$$F_{\text{statistic}} = \frac{\left(\dfrac{\text{RSS}_{\text{base}} - \text{RSS}_{\text{modified}}}{k_{\text{modified}} - k_{\text{base}}}\right)}{\left(\dfrac{\text{RSS}_{\text{modified}}}{n - k_{\text{modified}}}\right)}, \tag{4}$$

where RSS_{base} and $\text{RSS}_{\text{modified}}$ are the residual sum of the 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 were found to be realistic – the acceleration of the subject vehicle increased with an increase in the relative speed and vice-versa. The longitudinal gap was statistically insignificant for acceleration and following regimes, but significant for emergency braking and deceleration regimes. The acceleration regime occurs when a leader is faster than the subject vehicle. During the following regime, the subject vehicle unconsciously switches between acceleration and deceleration with positive and negative relative speed with the leader. In both these regimes, the longitudinal gap was found to be statistically insignificant, whereas it was significant for the emergency braking and deceleration regimes. The coefficient was positive, which indicates the acceleration of the subject vehicle with increasing longitudinal gap and deceleration with a shrinking longitudinal gap, and it is intuitive. Significant differences in the following behaviour were 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 varied with the leader–follower pair and regimes. Considering conscious reaction regimes, the relative speed coefficient was highest for the deceleration regime, followed by the emergency braking and acceleration regimes. The signs of relative speed coefficients for different vehicle-pair combinations are meaningful (positively correlated with response of the subject vehicle) for these three regimes. During the deceleration regime, the subject vehicle closes in with the leader with respect to the reduction in speed difference between the two (gap-narrowing). However, in the emergency braking regime, the subject vehicle becomes more alert about the spacing and shows increased sensitiveness towards the longitudinal gap compared to the deceleration regime. The coefficient of longitudinal gap of the TW–TW pair for the emergency braking regime (0.45) was 12.8 times that of the deceleration regime (0.035). This suggests that when a TW follows another TW, the influence of longitudinal gap in deciding the acceleration is highest for the emergency braking regime, followed by the deceleration regime.

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

Table 3. Modified acceleration model coefficients

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

*Represents intercepts/variables not statistically significant at 15%.

Table 4. Goodness of fit of modified acceleration model

Leader–follower interaction models	Sample size	R^2	MAE
TW–TW	10,187	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

Effect of local area concentration and its interaction with driving regimes: In addition to the relative position and speed between leader–follower pairs, the surrounding vehicles also influenced the response parameter due to weak lane-disciplined conditions. This effect can be captured by 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 the subject vehicle's LAC varied with driving regimes. During the acceleration regime, LAC and subject vehicle response were positively correlated. This indicates that if the concentration of the surrounding vehicles increases, the longitudinal response of the subject vehicle also increases. Considering the emergency braking regime, LAC and longitudinal response were negatively correlated for the subject vehicle car and positively correlated for TWs. Interestingly, this variable significantly affects the response of both cars and TWs, but in two different ways. Cars were found to decelerate with higher values of LAC because of greater confinement in deceleration cases. During deceleration, the magnitude of response of both cars and TWs was negatively correlated with LAC and the responsiveness was high for the TW–car pair followed by the car–car pair. However, when the subject vehicle was a TW, the coefficient of LAC was 6.2–19 times smaller compared to cars under the emergency braking regime. During the following regime, LAC was negatively correlated with acceleration for TW–TW, car–car and TW–car pairs, whereas it was positively correlated for the car–TW pair. The coefficient was highest for the TW–car pair. Thus, the influence of the surrounding vehicle on the subject vehicle varied based on the leader–follower pair and driving regimes.

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

The present study provides evidence of gap-seeking behaviour of TWs and following behaviour of cars. The responsiveness of both vehicles to different regime conditions also varied significantly. The concentration of the surrounding vehicles resulted in a reduction in speed for cars, whereas the TWs still managed to increase their speed with increasing LAC. The lateral gap maintained with the leader is a decisive factor for a longitudinal response when the leading vehicle is a TW. These findings prove that in mixed traffic, there exist strong and asymmetric interactions between TWs and cars that vary with driving regimes.

Summary and conclusion

In this study, we have developed a longitudinal response model of vehicles in mixed traffic under various driving regimes for various leader–follower interactions between cars and TWs. The model incorporating these parameters was 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 have been 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 the neighbourhood, etc.

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

Thus, it can be concluded that there exists asymmetric following behaviour across driving regimes, which varies with the leading and following vehicle types. This modelling scheme could reasonably segregate the performance of cars and TWs in a mixed traffic environment. In the present study, driving behaviour has been captured more realistically by considering the regimes of driving, leader–follower interactions and LAC. The use of trajectory data in deriving mixed traffic attributes and driving behaviour modelling adds novelty to the state-of-the-art car following models for mixed traffic conditions and can find potential applications 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 them to update the speed and position of a vehicle. Such micro-simulation models will help in a more realistic evaluation of level of service, safety and capacity. Thus, the models and findings from this study can be useful for developing simulation-based traffic management and operation strategies in future studies.

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