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# Modeling multiclass and no-lane-disciplined traffic streams using class-wise fundamental diagrams

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## Abstract

Traffic flow theory for a multiclass traffic stream is still in its infancy due to the limited understanding of associated chaotic traffic dynamics. The conventional theories and models do not consider the interactions and dynamics that occur in heterogeneous/mixed traffic conditions. Notably, the multi-class traffic flow consists of different vehicle types with varying sizes, speeds, and operational characteristics and shares the same road space without any lane discipline. Owing to the existence of a variety of vehicle classes, multiclass traffic flows may exhibit quite unique traffic flow dynamics. Particularly, the varying physical and dynamic properties of the vehicle classes lead to a gap-filling behavior, consequently violating lane discipline. Nevertheless, as different vehicle classes show distinct dynamic and kinematic characteristics, it can be postulated that there can be a class-wise fundamental diagram. Yet, there is no empirical evidence in the literature regarding the existence of a class-wise fundamental diagram. The present study critically examines the existence of a class-wise fundamental diagram for an urban traffic stream with a heterogeneous vehicle mix. In this direction, data were collected from a multiclass, no-lane-disciplined traffic stream on an urban midblock section in Guwahati, India. Further, the traffic stream was characterized using Area Density, Area Flow, and Road Space Freeing Rate (RFR). Using the empirical data, four existing macroscopic fundamental diagrams were calibrated considering class-wise RFR, Area Density, and Area Flow. The models were statistically evaluated for their goodness of fit with the empirical data. The findings of this study indicate the existence of the class-wise fundamental relationship and are capable of capturing the underlying dynamics, such as filtering behavior.

## 1. Introduction

Transportation in most developing countries is primarily multiclass and weakly follows the lane discipline. The traffic flow theory for such multiclass traffic streams is still in its infancy due to the limited understanding of chaotic traffic dynamics. Notably, the multi-class traffic flow consists of different vehicle types with varying sizes, speeds, and operational characteristics and shares the same road space without any lane discipline. Owing to the existence of a variety of vehicle classes, multiclass traffic flows may exhibit quite unique traffic flow dynamics. Particularly, the varying physical and dynamic properties of the vehicle classes lead to a gap-filling behavior, consequently violating lane discipline. It is to be noted that most of the macroscopic traffic flow models developed in the past were based on the assumption that the traffic is composed of homogeneous vehicles with comparable behavior and are essentially in the car-following condition (Jain & Coifman, 2005; May, 1994). Moreover, most of the efforts in building a mathematical relationship between the speed and the volume or density were applicable only to an uninterrupted traffic flow condition. Unfortunately, the existing models could not capture the unique dynamics of the multiclass traffic stream as they violate the above assumptions. Perhaps the multiclass traffic flow models have recently achieved potential research interest due to their capability to describe the dynamics of different vehicle classes and their interactions. These models could describe the puzzling traffic phenomena, such as the two capacity conditions, hysteresis, platoon dispersion, and so on, which were unanswered by the conventional models. Essentially, the multiclass models subdivide the traffic flow into flows of different user classes and model the dynamics of each homogeneous subgroup and their interactions. Each class encompasses a group of driver-vehicle entities that entitles a similar speed choice and driving behavior. Undeniably, most existing multiclass traffic flow models could capture the driver differences in a homogeneous traffic stream that lead to different speed choices (e.g., Gupta & Katiyar, 2007; Logghe & Immers, 2008; Wong & Wong, 2002).

Nevertheless, for a multiclass traffic stream prevalent in most developing countries, no significant research attempts have been exclusively made to investigate the possibilities of multiclass modeling, considering both the varying physical and dynamic properties of the vehicle classes. One of the difficulties in dealing with such a traffic stream is the direct relationship of the vehicles' physical dimensions to the traffic concentration. As the vehicles compete for the same travel spaces, the driver's speed depends on a perceived density rather than the homogeneous density in multi-class traffic modeling. Unfortunately, the conventional definitions of the traffic stream characteristics are unable to capture this aspect. Suvin & Mallikarjuna (2018) have redefined Edie's generalized definitions (Edie, 1963) of the traffic stream characteristics by considering both the physical as well as dynamic properties of the vehicles. A detailed discussion of the modified definitions is given in Section 4. Notably, the multi-class traffic flows are often evaluated by converting them into equivalent homogeneous traffic using several conversions, such as passenger car units (PCUs). However, PCUs do not capture the dynamic properties of the vehicle classes whose operational characteristics are significantly different (Nair et al., 2011). Therefore, developing a multiclass fundamental diagram is essential for precisely analyzing and modeling a mixed traffic stream.

One of the fundamental assumptions of multiclass traffic flow modeling is the existence of class-wise Fundamental Diagrams (FD). Though the multiclass traffic flow theory theoretically proves the existence of class-wise FD by considering the conservation of vehicle classes, the empirical existence of such a relationship is certainly a question. Furthermore, the multiclass consideration of the heterogeneous traffic stream is outside the scope of the existing framework of multiclass traffic modeling. Most studies base their models of heterogeneities on microscopic features, including temporal and spatial headways along with leader-follower interactions. These characteristics can only accurately represent heterogeneity if drivers of all vehicle classes follow the rules of the road (Bhavathrathan & Mallikarjuna, 2012). However, drivers compete for space on the road in developing countries such as India, where per-capita vehicle ownership is increasing extraordinarily, and their maximum share is two-wheelers. Due to the competition, two-wheeler riders use the space alongside the four-wheelers, which indefinite the values of flow and density. Thus, for a model to be useful in simulating Indian conditions, the class-wise FD must be incorporated, and the seeping behavior needs to be reflected in the model. The multiclass fundamental diagram for such conditions provides more control and management and helps adequate design and representations of the facilities. However, before endeavoring to adopt multiclass traffic flow theory for heterogeneous traffic flow conditions, it is important to critically investigate the existence of class-wise FD for a multiclass traffic stream. The present study hypothesizes that a class-wise fundamental diagram exists for a multiclass, no-lane-disciplined traffic stream and empirically investigates the

validity of the hypothesis. While the focus of this research centers on Guwahati, India, the lessons and findings from this investigation hold value for rapidly urbanizing regions across the globe, including parts of Australia and New Zealand. As these regions encounter more diverse traffic flow due to globalization and urbanization, understanding the nuances of multiclass traffic is increasingly crucial.
The remainder of the paper is organized as follows. Section 2 briefly reviews the multiclass traffic flow theory and its advancements. In Section 3, the data collection procedure and the post-processing of the data are described. Section 4 discusses the methodology of the present study. The findings from this study are discussed in Section 5. Section 6 summarizes and concludes the paper.

# 2. Background

The development of traffic flow models dates back to 1950s with the introduction of the first dynamic traffic flow model by Lighthill & Whitham (1955), and Richards (1956) introduced the LWR model. The LWR model describes the traffic on a link using the conservation law, an equilibrium speed-density relationship, and the fundamental equations of the traffic flow. This equilibrium relation $Q_e(k)$ is better known as the fundamental diagram for the traffic stream (Leuven et al., 2000). The LWR model is known to have limitations such as; *i*) the equilibrium speed-density relationship is the only mode to measure the speed, and no fluctuations of speed around the equilibrium values are allowed (Gupta & Katiyar, 2007), *ii*) the LWR model is not applicable to the non-equilibrium conditions like stop and go, and multiclass traffic compositions (Logghe & Immers, 2008). Many efforts were made to extend the LWR model to capture the various empirically observed traffic dynamics. In fact, several researchers (Kerner et al., 1993; Payne, 1971; Phillips, 1979; H. M. Zhang, 1998) have suggested that higher-order traffic flow models overcome the LWR model's drawbacks. Yet, these models could not explain some perplexing traffic phenomena observed on the highway, such as the two-capacity or reversed-lambda state, hysteresis, platoon dispersion, and so on.
In order to model the above dynamics, researchers started developing the multi-class continuum models considering different vehicle classes with varying dynamic properties (Fan & Work, 2015; Gupta & Katiyar, 2007; Hoogendoorn & Bovy, 2000; Logghe & Immers, 2008; Ngoduy, 2011; van Lint et al., 2008; van Wageningen-Kessels, 2016; van Wageningen-Kessels et al., 2014; Wong & Wong, 2002). By separating the user classes and their specific flow characteristics, researchers were able to improve the accuracy and the descriptive power of the macroscopic traffic flow models (Hoogendoorn & Bovy, 1998). However, the analyses were limited to a small set of specific problems, and not all the currently known models were included in multiclass modeling (van Wageningen-Kessels, 2016). Wong & Wong (2002) presented a multiclass traffic flow model by extending the LWR model for different user classes having different speed choices. Chanut & Buisson (2003) have contributed an approach in which vehicles are differentiated by their lengths and speed choices in free-flow conditions. Gupta & Katiyar (2007) proposed a new higher-order continuum model by extending Berg's model (Berg et al., 2000) for a multiclass traffic stream. Gupta & Katiyar (2007) also differentiated the vehicle classes based on speed choices. van Lint et al. (2008) proposed a new multiclass model named "FASTLANE" that specified the heterogeneity of the traffic stream in a more sensible way. FASTLANE differs from previous multiclass first-order macroscopic traffic models in estimating traffic characteristics in terms of state-dependent passenger-car equivalents. Later, van Wageningen-Kessels et al. (2014) showed the distinctive properties of the FASTLANE in a simulation environment. A numerical scheme for solving the multi-class extension of the LWR model was proposed by Zhang et al. (2009), which was a high order weighted, essentially non-oscillatory (WENO) scheme. Ngoduy (2011) showed that hysteresis

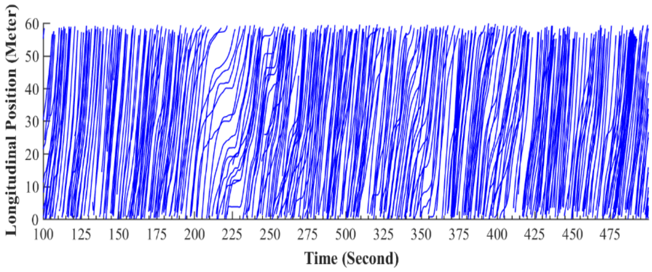
transitions and the wide scattering could be reproduced by a multiclass first-order model with a stochastic setting in the model parameters. Nair et al. (2011) developed a multiclass traffic flow model for multiclass traffic without lane discipline based on an analogy of fluid flow through a porous medium. The model was able to explain the filtering behavior (a special case of overtaking where small vehicles will be moving even after all the larger vehicles are totally stopped) of the smaller vehicles through the available gaps (pores) in the congested traffic stream. Fan & Work (2015) presented a multi-class model to capture overtaking and filtering in highly multiclass traffic stream. Sreekumar et al. (2022) proposed a multi-class traffic flow model by quantifying both viable as well as accessible opportunities for the individual vehicle classes to transverse downstream. Noël et al. (2020) used the Lattice Boltzmann Method to model the multi-class and heterogeneity in the traffic flow. The results from the studies were able to replicate the results of Drake's model (Drake & Schofer, 1966). A few studies have focused on multi-dimensional continuum models of traffic flow to incorporate the impact of the lateral influences of road edges in the multi-class traffic flow. Herty et al. (2018) proposed a two-dimensional continuum model of traffic flow where they used the lateral speed of the traffic stream and defined that as a function of density. Later, Balzotti & Göttlich (2021) extended this work and proposed a two-dimensional LWR-type macroscopic traffic model for multi-class traffic. Vikram et al. (2022) proposed a two-dimensional continuum traffic flow model, where they incorporated driver behavior in longitudinal and lateral directions of a road. Later, Mohan & Ramadurai (2021) proposed a continuum model based on a three-dimensional flow-concentration surface for multi class traffic. They used the variations of flow for each vehicles class using a three-dimensional function of class density with occupied road space by other vehicle classes instead of conventional flow-density relationship.

Despite all these efforts, it is still unclear whether there exists a class-wise FD for a multiclass traffic stream prevalent in most developing countries. Although, an efficient and reliable traffic flow model is the prerequisite for developing an effective transport management system from a macroscopic perspective (Kotsialos & Papageorgiou, 2001). Thus, before employing a traffic flow model in practice, it is essential to calibrate it against real traffic data. The literature clearly states that, apart from the dynamic characteristics of the vehicle classes, it is important to consider the physical aspects of a vehicle class for a better representation of the multiclass traffic stream. It is also evident from the literature that the existence of a class-wise fundamental diagram is an important criterion for multi-class traffic flow modeling. However, no empirical evidence is shown in the literature for the existence of a class-wise fundamental diagram. Most of the above modeling attempts were theoretical or assumed a fundamental diagram exists for the vehicle classes. Hence there is clear scope for the research in the direction of the empirical investigation of the class-wise fundamental diagram after appropriately characterizing the multiclass traffic stream.

# 3. Data collection and post-processing

Traffic data have been collected by recording the video footage from the multiclass, no-lane-disciplined traffic stream. An urban midblock section located at Dispur, Assam, was selected for the data collection. A camera was placed over a nearby foot over-bridge in such a way that the camera's field of view could cover the maximum road length. The video was recorded for a duration of 2 hours, between 2pm-4pm during which traffic was moving in both free and forced conditions. The weather was clear with no rain and the average temperature during this time was around 35 degrees Celsius. This urban midblock section was chosen as a representative case, reflecting common traffic conditions found in many parts of urban India. Such conditions, while rooted in the Indian context, exhibit patterns that parallel other Asian cities and even some rapidly urbanizing cities outside Asia, such as in Australasian. The vehicle trajectories were extracted from the video footage using an image-processing tool, SAVETRAX (Suvin & Mallikarjuna, 2022; Venthuruthiyil & Chunchu, 2020). The extracted trajectories were reconstructed using the methodology proposed by (Venthuruthiyil & Chunchu (2018, 2022). Figure 1 shows a sample of the trajectory data considered in the present study. The average traffic composition observed during the 2-hr period was 51.6% LMV, 32.3% Bike, 8.6% HMV, and 7.5% Auto- Rickshaw.

**Figure 1:Sample trajectory data considered in the present study**




# 4. Methodology

This section is divided into three subsections. In the first part, a brief introduction to the concepts of the multiclass traffic flow theory is given. The second part discusses the process of the characterization of the multiclass traffic stream. In the third part, the calibration procedure of the fundamental diagram is explained.

## 4.1. Multiclass traffic flow theory

Multiclass traffic flow theory states that the conservation equation could be applied separately to different vehicle classes. Besides, the multiclass traffic flow modeling also assumes the distribution of speed around the equilibrium speed, corresponding to a total density, due to the presence of '*M*' user classes with different speed choice behavior. It has been assumed that the variation of the speed around the mean speed decreases with increasing density due to the tighter interaction between the vehicle classes. The total density corresponding to a multiclass traffic stream is given by,

$$\rho(x,t) = \sum_{m=1}^{M} \rho_m(x,\mathrm{t}) \tag{1}$$

Where, $\rho_m(x,t)$ is the density of user class '$m$' in the time-space domain. The traffic stream characteristics such as the flow, speed, and density of a particular vehicle class are related as,

$$q_m(x,t) = \rho_m(x,t) \times v_m(x,t) \qquad \forall m = 1,2,3,....,M \tag{2}$$

Based on the driving behavior of a particular vehicle class, the conservation law could be applied to each vehicle class as,

$$\frac{\partial \rho_m(x,t)}{\partial t} + \frac{\partial q_m(x,\mathrm{t})}{\partial x} = 0 \qquad \forall m = 1,2,3,....,M \tag{3}$$

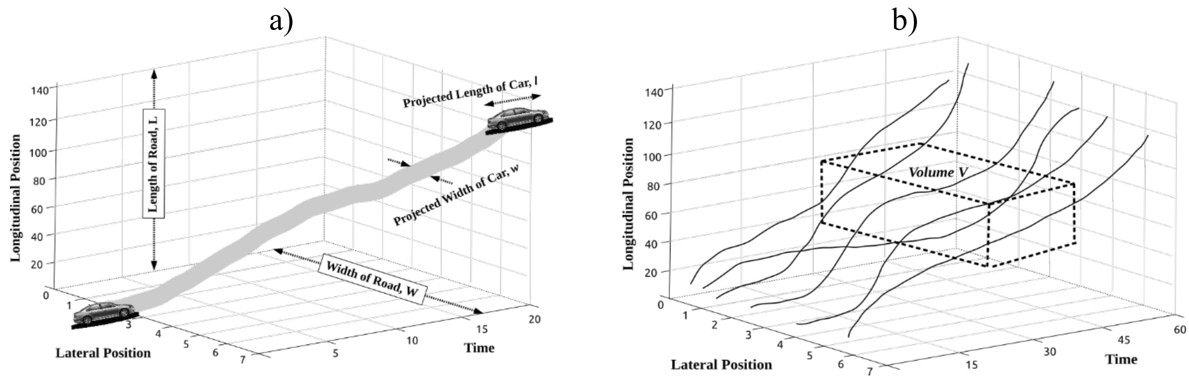
Equation 3 states that the density changes according to the balance between the inflow and outflow of vehicles of user class $m$ along a topographically homogeneous highway section.

As discussed earlier, the conventional measures of the traffic stream characteristics could not be applied to the multiclass traffic stream since the dimensions of the vehicle and the no-lane-disciplined driving significantly influence the traffic characteristics. Moreover, the hindrance to the nearby traffic by the presence (time spent in the traffic stream) of a smaller vehicle (say, Bike) and a larger vehicle (say, Truck) would be significantly different. Considering this fact, the present study adopted the modified generalized definitions proposed by Venthuruthiyil & Chunchu (2018) for defining the traffic stream characteristics. A detailed discussion of the modified definitions is given in the following section.

## 4.2. Modified generalized definitions for heterogeneous traffic stream

In order to capture the variability in the vehicles' dimensions and the no-lane-disciplined driving actions, Suvin & Mallikarjuna (2018) gave modified Edie's generalized definitions of the traffic stream characteristics by incorporating an additional dimension of the space. All the heterogeneous traffic dynamics were assumed to take place in a three-dimensional time-space continuum, which encompasses two dimensions of space and a time dimension. The width of the vehicle, as well as the road, has been incorporated into Edie's generalized definition for capturing the vehicle dimensions and the no-lane-disciplined actions, respectively. Figure 2 shows the three-dimensional trajectory and the time-space continuum considered in the definitions. The newly defined traffic stream characteristics were named the 'Area Density', 'Area Flow', and the 'Road Space Freeing Rate (RFR)'.

**Figure 2: a) The path followed by a car in the time-space continuum; b) Three-dimensional trajectories and the time-space continuum**




The area density measures the crowdedness of the traffic and is defined as,

$$Area\ Density = \frac{Sum\ of\ the\ areas\ of\ the\ 'time-space'\ region\ occupied\ by\ each\ vehicle}{Volume\ of\ the\ 'time-space'\ continuum}$$

$$\rho_A = \frac{\sum_{i=1}^{n} t_i \times w_i}{L \times W \times T} \tag{4}$$

Similarly, the area flow, which is the demand for the supplied infrastructure, is defined as,

$$Area\ Flow = \frac{Sum\ of\ the\ areas\ of\ the\ projected\ path\ of\ each\ vehicle}{Volume\ of\ the\ 'time-space'\ continuum}$$

$$q_A = \frac{\sum_{i=1}^{n} d_i \times w_i}{L \times W \times T} \tag{5}$$

The ratio of the area flow to the area density is termed as the road space freeing rate (RFR) and is defined as,

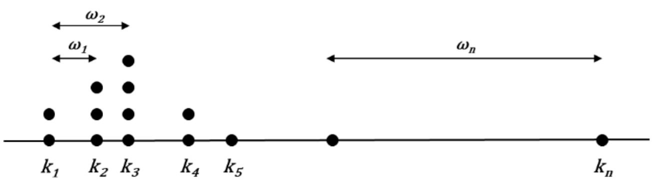
$$RFR = \frac{q_A}{\rho_A} = \frac{\sum d_i \times w_i}{\sum t_i \times w_i} \tag{6}$$

Using the above definitions, the traffic stream characteristics were obtained from the extracted trajectories. The class-wise Area Flow, RFR, and Area Densities were also calculated by applying the same definitions to the class-wise data. The existing single regime models were calibrated using the empirical data, and the details of the calibration procedures are discussed in the following section.

## 4.3. Calibration of the traffic flow models

Calibration of the mathematical models with empirical data is the process of estimating the model parameters as accurately as possible. Therefore, calibration is a critical process that decides model prediction capability. Several optimization tools have been employed as a calibration method to minimize the deviations between the empirical data and the model form. Qu et al. (2015) have stated that the inaccuracy of single-regime models arises not solely because of the improper functional forms but also of the bias in the collected data. It is evident from many of the empirical macroscopic traffic studies that the traffic data is heavily biased to the region below a certain density value (Gomes & Horowitz, 2009; Wu et al., 2011). Considering the possibility of bias in the data, Qu et al. (2015) proposed a novel calibration approach, the so-called Weighted Least Square Method (WLSM), that assigns certain weights to each data point based on the distance to the nearby points on the left and right side of the subject point (Figure 3). The WLS method was able to resolve the model calibration issues due to the selection bias in the data sample. The present study follows the WLSM for model calibration.

**Figure 3: General Weight Determination Method**




The procedure of the WLSM is as follows for all the speed-density observations ($v_i$, $k_i$), where $k_i$ and $v_i$ are the $i^{th}$ density and speed observations, and a weight $w_i$ is assigned based on the closeness of nearby observations. The step-by-step procedure followed in the weight estimation is shown below.

*Step 1*: Rank the observations in terms of their densities. We thus have,

$$(v_1,k_1), (v_2,k_2), (v_3,k_3), (v_4,k_4)\dots, (v_i,k_i),\dots, (v_n,k_n),$$

Where, $k_1 \le k_2 \le \dots\dots \le k_i \le \dots\dots \le k_n$

*Step 2*: Define $\hat{u}$ as the largest index '$i$' that corresponds to the same density as $k_1$, that is,

$$\hat{u} := \arg\max\{i = 1,2,...,n \mid k_i = k_1\}$$

Then,

$$\varpi_i = \frac{k_{\hat{u}+1} - k_1}{\hat{u}}, \qquad i = 1,2,...,\hat{u}$$

*Step 3*: Define $u = \hat{u} + 1$, define $\hat{u}$ as the largest index '$i$' that corresponds to the same density as $k_u$ that is,

$$\hat{u} := \arg\max\{i = u, u+1, \mathrm{u}+2,...,n \mid k_i = k_u\}$$

$$\varpi_i = \frac{k_{\hat{u}+1} - k_{u-1}}{2(\hat{u} - u + 1)}, \qquad i = u, u+1, \mathrm{u}+2,...,\hat{u}$$

And repeat *Step 3*. Else,

$$\varpi_i = \frac{k_m - k_{u-1}}{m - u + 1}, \qquad i = u, u+1, u+2,...,n$$

And stop.

Apart from the above considerations, the present study utilizes a robust least squares approach to remove the outliers in the speed observations (Cleveland, 1979). It is usually assumed that the errors follow a normal distribution, and the occurrence of extreme values are rare. The main disadvantage of using simple least-squares fitting is its sensitivity toward the outliers. Outliers have a large influence on the fit because squaring the residuals magnifies the

effects of these extreme data points. To minimize the influence of outliers, the robust weighted least-squares regression was considered. This method minimizes the weighted sum of squares, where the weight given to each data point depends on how far the point is from the fitted line. Points near the line get full weight, and those farther from the line get a reduced weight. Robust fitting with bi-square weights uses an iteratively reweighted least-squares algorithm and follows this procedure:
Step 1: Fit the model with weighted least squares.
Step 2: Compute the adjusted residuals and standardize them. The adjusted residuals are given by

$$r_{adj} = \frac{r_i}{\sqrt{1-h_i}}$$

$r_i$ is the usual least-squares residual ($r_i = y_i - \hat{y}_i$) and $h_i$ is the leverage that adjusts the residuals by reducing the weight of high-leverage data points. The standardized adjusted residuals are given by

$$u = \frac{r_{adj}}{Ks}$$

*'K'* is a tuning constant equal to 4.685, and '$s$' is the robust variance given by $\frac{MAD}{0.6745}$ based on the idea that E[MAD] = 0.6745 for the standard normal conditions, where *MAD* is the median absolute deviation of the residuals (Holland & Roy, 1977; Seheult et al., 1989).
Step 3: Compute the robust weights as a function of $u$. The bi-square weights are given by

$$w_i = \begin{cases} \left(1-(u_i)^2\right)^2 & |u_i| < 1 \\ 0 & |u_i| \geq 1 \end{cases}$$

Step 4: If the fit converges, stop the iteration. Otherwise, perform the next iteration of the fitting.
In this study, different single regime traffic flow models were calibrated against the empirical data using the Robust WLSM. The selection of the macroscopic traffic flow models for calibration was done by considering different model categories proposed by Carey & Bowers (2012). They reviewed different macroscopic traffic flow models and categorized them based on certain properties of the models. We have considered models from these different categories to ensure that the fit of a model with the empirical data is not only due to the functional form of the model. Table 1 shows the different models considered for the calibration and the category. Calibration was performed for each model considering the class-wise RFR and area density as well as the class-wise RFR and the total area density of the traffic stream. The calibration results and the discussions are given in the following section.

**Table 1: Macroscopic Single Regime Models Considered for Calibration**

| Model Category | Model | Model Form |
|---|---|---|
| Flow-Density functions that have the jam density at +∞, unless truncated | Drake's Model | $v = v_f \times \left[\exp\left(-\frac{1}{2} \times \left(\frac{k}{k_c}\right)^2\right)\right]$ |
| | Papageorgiou's Model | $v = v_f \times \left[\exp\left(-\frac{1}{m} \times \left(\frac{k}{k_c}\right)^m\right)\right]$ |
| Flow-Density functions that have the jam density and a parameter for the gradient at jam density | Newell's Model | $v = v_f \times \left[1-\exp\left(\frac{c_j}{v_f} \times \left(1-\frac{k_j}{k}\right)\right)\right]$ |
| Non-classical Flow-Density functions | Del Castillo's Model | $v = v_f \times \left[1-\exp\left(1-\exp\left(\frac{c_j}{v_f} \times \left(\frac{k_j}{k}-1\right)\right)\right)\right]$ |

# 5. Results and discussions

The calibration results support the hypothesis that there exists a class-wise fundamental diagram for a multiclass, no-lane-disciplined traffic stream. Figure 4 shows the calibrated models with the class-wise RFR and Area Density. Table 2 shows the fit statistics corresponding to each model calibrated with the class-wise RFR and Area Density. It is apparent that most of the models give a satisfactory fit to the empirical observations. It is evident that Del Castillo's model is getting a better fit to the data and getting better $R^2$ and RMSE for all the vehicle classes. Similarly, Figure 5 and Table 3 show the calibration results of the models with the class-wise RFR and the total Area Density of the traffic stream. The fit results are satisfactory and support the hypothesis of this study. Table 3 shows a similar trend as Del Castillo's model is getting the best statistics for all the vehicle classes and total traffic. The $R^2$ and RMSE in total traffic and LMVs are higher than other vehicle classes. LMV is getting the best $R^2$ and RMSE values compared to the other vehicle classes show that LMVs best represent the total traffic.

**Figure 4: Variation of the RFR of a particular vehicle class with the area density of that particular vehicle class**

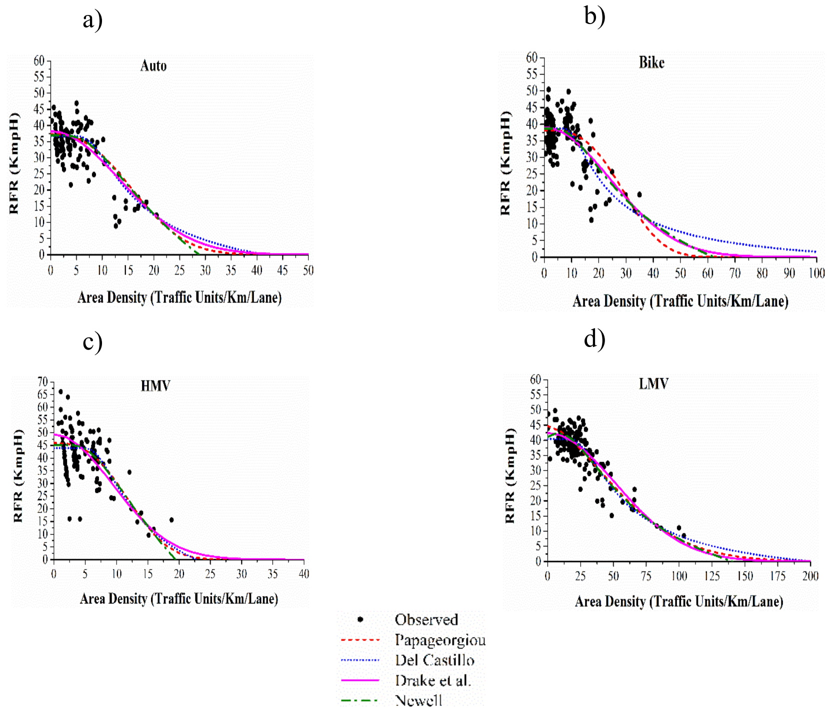



**Table 2: Result of model calibration with the empirical data considering the class-wise density**

| Model | Auto-Rickshaw | | Bike | | HMV | | LMV | |
|---|---|---|---|---|---|---|---|---|
| | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE |
| ***Drake et al.*** | 0.8852 | 1.629 | 0.8841 | 1.8340 | 0.8479 | 2.390 | 0.9545 | 2.342 |
| ***Papageorgiou*** | 0.8895 | 1.605 | 0.8983 | 1.731 | 0.856 | 2.336 | 0.9464 | 2.552 |
| ***Newell*** | 0.8975 | 1.546 | 0.8882 | 1.816 | 0.8558 | 2.337 | 0.9487 | 2.498 |
| ***Del Castillo*** | 0.9012 | 1.5780 | 0.8841 | 1.8480 | 0.8650 | 2.261 | 0.9587 | 2.239 |

**Figure 5: Variation of the RFR of a particular vehicle class with the total area density of the traffic stream**

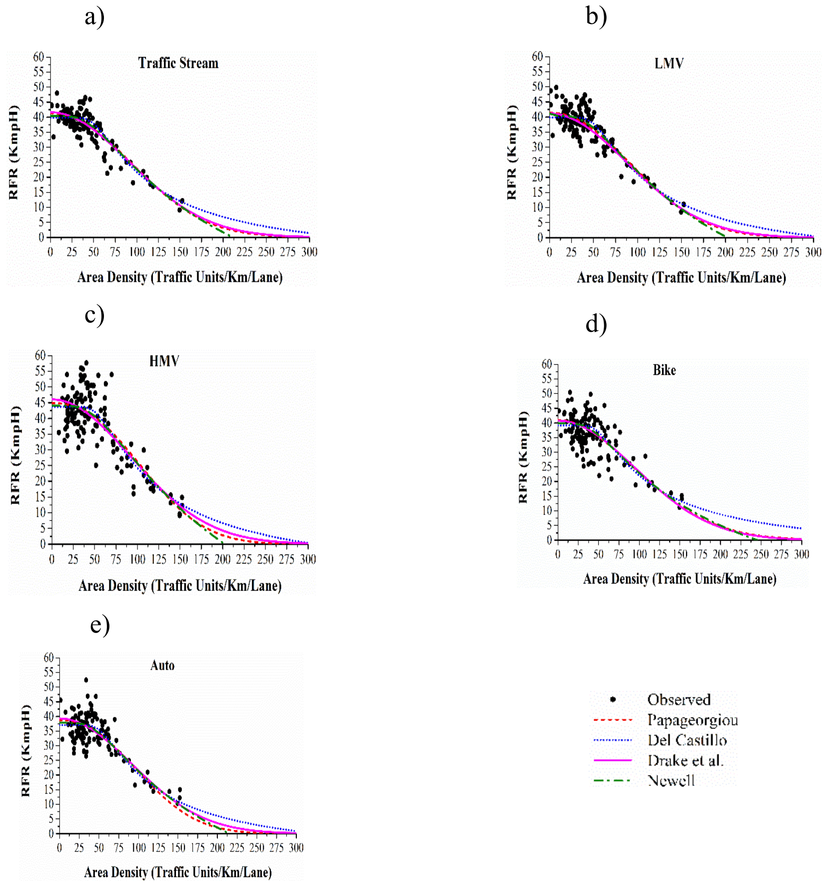



**Table 3: Result of model calibration with the empirical data considering the total density**

| Model | Total Traffic | | Auto-Rickshaw | | Bike | | HMV | | LMV | |
|---|---|---|---|---|---|---|---|---|---|---|
| | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE | $R^2$ | RMSE |
| ***Drake et al.*** | 0.9586 | 2.369 | 0.8966 | 3.828 | 0.8773 | 3.899 | 0.8791 | 5.245 | 0.953 | 2.673 |
| ***Papageorgiou*** | 0.9597 | 2.340 | 0.9009 | 3.748 | 0.8756 | 3.927 | 0.8831 | 5.157 | 0.9549 | 2.619 |
| ***Newell*** | 0.9605 | 2.302 | 0.8948 | 3.844 | 0.8809 | 3.827 | 0.8809 | 5.183 | 0.9541 | 2.631 |
| ***Del Castillo*** | 0.9611 | 2.296 | 0.9137 | 3.497 | 0.8826 | 3.813 | 0.8917 | 4.964 | 0.9529 | 2.666 |

Figure 6 shows the multiclass fundamental diagram of the traffic stream calibrated with different macroscopic single regime models. This figure clearly shows the higher maneuverability of the Bike and its creeping behavior during higher-density conditions. Further, we have investigated the additive property of the Area Densities of vehicle classes as shown in Equation (1). Corresponding to a given total Area Density ($\rho_{Total}$) the class-wise RFR ($RFR_m(\rho_{Total})$) was estimated from each of the model equations. The estimated $RFR_m(\rho_{Total})$ was applied to the class-wise model equations and estimated the class-wise Area Density ($\rho_m$). The class-wise Area Densities were added together to get $\sum\rho_m$ and compared with the $\rho_{Total}$. The difference between $\sum\rho_m$ and $\rho_{Total}$ was measured with the Mean Absolute Percentage Error (MAPE) for all the models.
Figure 6 shows the multiclass fundamental diagram for the multiclass traffic stream calibrated with different models. Multiclass traffic flow theory assumes that, with an increment in the traffic density, the speed of all vehicle classes converges due to the higher interactions. The

same could be observed in the figure except for the smaller vehicles since they exhibit creeping behavior, which is another property of the multiclass traffic stream. Tables 4 & 5 contain the MAPE values of all the models for different vehicle classes for two different total area densities. The results show that the MAPE for Del Castillo's model is the least among all for both scenarios. Therefore, it can be stated that Del Castillo's Model shows the best results and the least error.

**Figure 6: Speed and flow variation for different vehicle classes in response to the total density**

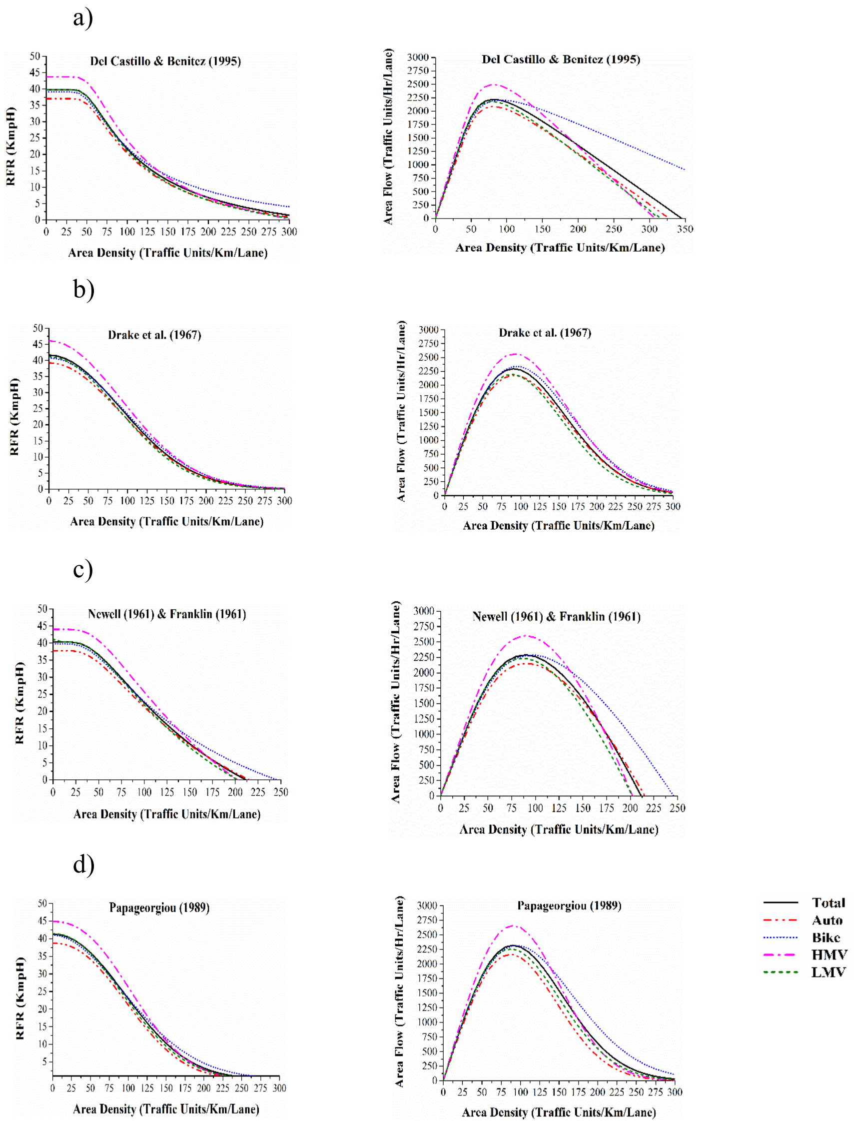



**Table 4: Error analysis between the total area density and the class-wise area densities (ρ_Total = 50 Traffic Units/Km/Lane)**

| Model | Auto-Rickshaw | | Bike | | HMV | | LMV | | *MAPE* |
|---|---|---|---|---|---|---|---|---|---|
| | $RFR_m(\rho_{Total})$ | $\rho_m$ | $RFR_m(\rho_{Total})$ | $\rho_m$ | $RFR_m(\rho_{Total})$ | $\rho_m$ | $RFR_m(\rho_{Total})$ | $\rho_m$ | |
| ***Papageorgiou*** | 34.17 | 7.35 | 35.32 | 14.48 | 40.45 | 6.61 | 35.87 | 27.72 | 12.32 |
| ***Del Castillo*** | 35.51 | 7.34 | 36.92 | 10.29 | 42.18 | 6.57 | 37.83 | 27.42 | 3.24 |
| ***Drake et al.*** | 33.84 | 6.64 | 35.47 | 10.5 | 39.76 | 6.11 | 35.04 | 34.04 | 14.58 |
| ***Newell*** | 34.32 | 7.54 | 35.80 | 10.88 | 40.80 | 6.47 | 36.45 | 27.17 | 4.12 |

**Table 5: Error analysis between the total area density and the class-wise area densities (ρ_Total = 180 Traffic Units/Km/Lane)**

| Model | Auto-Rickshaw | | Bike | | HMV | | LMV | | MAPE |
|---|---|---|---|---|---|---|---|---|---|
| | $RFR_m(\rho_{Total})$ | $\rho_m$ | $RFR_m(\rho_{Total})$ | $\rho_m$ | $RFR_m(\rho_{Total})$ | $\rho_m$ | $RFR_m(\rho_{Total})$ | $\rho_m$ | |
| ***Papageorgiou*** | 3.88 | 26.57 | 6.93 | 39.66 | 5.18 | 18.13 | 4.68 | 114.4 | 10.42 |
| ***Del Castillo*** | 7.76 | 24.91 | 10.39 | 40.42 | 8.80 | 16.93 | 7.76 | 104.5 | 3.76 |
| ***Drake et al.*** | 5.65 | 26.23 | 6.67 | 45.05 | 6.76 | 18.52 | 5.06 | 106.8 | 9.22 |
| ***Newell*** | 4.99 | 24.96 | 7.66 | 44.5 | 4.45 | 17.86 | 3.64 | 118.3 | 14.23 |

# 6. Conclusion and future scope

The present study investigates the existence of the class-wise fundamental diagram for a multiclass, no-lane-disciplined traffic stream. Modified generalized definitions were used for the traffic stream characteristics by considering both the physical and dynamic properties of the vehicles of different classes. These definitions capture the vehicle heterogeneity as well as the no-lane-disciplined actions. This study characterizes the multiclass, no-lane disciplined traffic stream using characteristics such as Area Density, Area Flow, and Road Space Freeing Rate (RFR). The traffic data used in the study was collected by recording the video footage from a multiclass, no-lane-disciplined traffic stream on an urban midblock section in Guwahati, India. The vehicle trajectories were extracted using an image-processing tool, the Traffic Data Extractor (TDE), and extracted trajectories were reconstructed using an approach proposed by Venthuruthiyil & Chunchu (2018). Various single regime traffic flow models were calibrated against the empirical data collected from an urban arterial. Later, the RFR of each vehicle class were plotted against the class-wise area density and total density in figure 4 and 5, respectively. The creeping behavior of two-wheelers under multi-class traffic conditions can be visible in the figures. Later, RFR and Flow were plotted against total density, and the models were calibrated using a Robust Weighted Least Square Method. The fundamental assumption of the multiclass traffic flow theory, i.e., the total traffic density as the summation of the densities of individual vehicle classes, was tested with different models. An error analysis between the class-wise area densities and total area densities was conducted at two different total density values.

The finding from this study indicates that there exists a class-wise fundamental diagram for a multiclass traffic stream, and it follows the fundamental assumptions of the multiclass traffic flow theory. The analysis shows that Del Castillo's model gives a better representation of the multiclass, no-lane-disciplined traffic stream among the studied traffic flow models. Del Castillo's model produces the minimum MAPE for free and forced flow conditions. Besides, Del Castillo's model captures the seeping behavior of the smaller vehicles at higher density levels in a comparatively better way.

The present study on the dynamics of a multiclass, no-lane-disciplined traffic stream in Guwahati, India, holds relevance for the Australasian transport research community due to shared challenges in multiclass traffic flow dynamics despite Australia's generally good lane discipline. The study's insights offer valuable implications for Australasian cities, considering their urban traffic conditions with high density and complex dynamics. Additionally, considering a heterogeneous vehicle mix in the study provides lessons for managing interactions between different vehicle classes in Australasian cities. Even in disciplined lane environments, understanding multiclass behavior remains essential for optimizing traffic flow and safety measures in Australasia.

While the site served as a suitable case study for investigating multiclass, no-lane-disciplined traffic flow, it represents the diversity of traffic conditions in Assam, India, and other regions in Asia. Our research methodology and approach offer opportunities for generalization and transferability of the findings. By considering both vehicles' physical and dynamic properties, the calibration of class-wise fundamental diagrams can be adapted to study similar traffic conditions in other urban centers, including those in Australasia. In conclusion, while grounded in a specific location, our research offers a basis for exploring multiclass traffic dynamics in diverse urban contexts, including those in Australasia.

The present study can be extended in multiple directions. Other macroscopic traffic models can be used in the step of calibration of the empirical data. A new multiple-regime model can be plotted based on the dataset, which can minimize the error and perform better for a specific dataset. A broader classification of the vehicle classes can be used in future studies. Although our study provides insights into the average traffic composition in the studied location, variations may exist in other sites in the region. We view our findings as a starting point for understanding multiclass traffic dynamics in similar regions rather than a definitive representation of all traffic conditions. However, we emphasize the need to consider each location's unique traffic characteristics when applying our findings.

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