Study of Traffic Simulation Model for Heterogeneous Traffic

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***Abstract*—Mixed-mode traffic, with its diverse vehicle types and varying attributes, holds substantial significance compared to homogeneous traffic scenarios. While homogeneous traffic comprises vehicles with similar characteristics, mixed-mode traffic mirrors real-world road complexities, including cars, trucks, rickshaws, motorcycles, and more. Recognizing the value of mixed-mode traffic fosters comprehensive and realistic transportation planning tailored to each vehicle type's unique needs. In our study, we analyzed macroscopic parameters like traffic flow, speed, and density using the SUMO traffic simulator, affirming its efficacy for modeling mixed-mode traffic. As, the car-following parameters of mixed-mode traffic have been manually tuned in our study for SUMO. So, it opens up possibilities for using machine learning models to predict the parameters for further improvements.**

***Index Terms*—Mixed mode traffic, Car-following model, Traffic simulation, Intelligent Transportation System**

I. Introduction

Intelligent Transportation System (ITS) technologies leverage Information and Communication Technology (ICT) to gather and process data on current and future traffic conditions. Utilizing advanced information retrieval and computation methods, ITS manages transportation networks efficiently. In the broader realm of ITS, Traffic Modeling, dating back to the 1940s, employs mathematical equations to depict road traffic, incorporating variables like flow, density, and speed. These models, addressing spatial and temporal variations, facilitate the estimation of present and future traffic states, prediction of patterns, and detection of changes in traffic behavior. Traffic Modeling yields scientific insights and tools crucial for optimizing signal timings, assessing road capacity, evaluating ITS technologies, aiding emergency planning, and promoting sustainable transportation strategies. By concentrating on mixed-mode traffic, the research aims to comprehensively analyze the interactions and dynamics among diverse transportation modes, such as cars, trucks, mopeds, pedestrians, and more. This approach captures the heterogeneity and inter-dependencies among modes, offering insights into travel patterns, congestion hotspots, and mode choice behavior, ultimately contributing to the development of more efficient, safe, and sustainable transportation systems.

The primary contributions of the paper are as follows:

- A comprehensive study of the aggregate behavior of mixed-mode traffic is conducted.
- Investigate the macroscopic parameters of mixed-mode traffic and study how they are correlated with each other.
- The research contributes by simulating mixed-mode traffic on a traffic simulator, allowing for the analysis of macroscopic parameters such as traffic flow, speed, and density. The car-following model parameters are tuned to minimize discrepancies between observed macroscopic parameters in the dataset and those simulated in a mixed-mode traffic scenario, enhancing the accuracy and applicability of the model.

  The paper is organized as follows: Section II presents the state-of-the-art of heterogeneous vehicular traffic flow modeling.

  Section III defines the problem related to mixed-mode traffic along with the assumptions. Section IV discusses the data sets used for the experiment. Section V describes the experimental setup of the research and analyzes its results and section VI concludes the paper by outlining the key findings and recommending future research directions.

II. RELATED WORK

Real-world traffic comprises a diverse mix of vehicles and drivers, resulting in heterogeneous traffic flow with varying characteristics, such as size, speed, and driver behavior. To model this, traffic dynamics are analogized to hydrodynamic theory, treating vehicle flow like fluid movement in a pipe. This macroscopic approach simplifies the modeling process, requiring fewer variables and enabling faster decision-making. The main variables used for describing its behavior are traffic flow, road density and average speed of vehicles. Traffic flow expresses the number of vehicles passing a location in a unit time [1]. If the number of vehicles measured by a sensor in an interval $\triangle t$ is N(t), the flow of traffic is expressed as:

$$q(t) = \frac{N(t)}{\triangle t} \tag{1}$$

Road density expresses the number of vehicles that are on a section of the road [1]. If the section of road on which the density is measured is given by $\triangle x$ and the number of vehicles that are on this section is given by N(t), road density is the ratio between:

$$\rho(x,t) = \frac{N(t)}{\triangle x} \tag{2}$$

where $N(t)$ is number of vehicles occupying part of the unit section during the specified time t and $\triangle x$ is the length of section in 'm' or 'Km'.

The average speed of vehicles expresses the average road speeds of vehicles that are on a section of the road [1]. In practice, the value of the average speed (V_{m}) is obtained by averaging the speeds of vehicles passing over a sensor for a fixed period of time (considering a number K of measurements):

$$V_{\mathrm{m}} = \sum_{i=1}^{K} \frac{V(t_{\mathrm{i}})}{K} \tag{3}$$

where V_{m} is average speed of vehicles and $V(t_{\mathrm{i}})$ is the speed of a vehicle at time t.

In the context of macroscopic approaches, the focus shifts from the dynamics of individual vehicles to the dynamics of macroscopic quantities [5]. Specifically, the vehicle density $\rho(x,t)$ and average velocity $v(x,t)$ are considered as functions of space (x) and time (t). These quantities are obtained by averaging over a sufficiently large spatial region. Since the number of vehicles in a road segment can only change through vehicles entering or leaving the segment, a continuity equation holds for ρ and v

$$\frac{\partial \rho}{\partial t} + \frac{\partial}{\partial x}(\rho v) = 0 \tag{4}$$

where ρ is the density of the fluid, v is the velocity in the x-direction.

As one of the classic car-following models, Krauss model is a microscopic, space-continuous one, and it was established based on the safe speed [5].

In each time step the vehicle‘s speed is adapted to the speed of the leading vehicle in a way that yields to a collision-free system behaviour within the following simulation step(s).

$$V_{\mathrm{safe}}(t) = V_{\mathrm{l}}(t) + \frac{g(t) - V_{\mathrm{l}}(t)\tau}{\frac{V_{\mathrm{l}}(t)+V_{\mathrm{f}}(t)}{2b} + \tau} \tag{5}$$

where

- $V_{\mathrm{safe}}(t)$: Maximum Safe velocity in time t
- $V_{\mathrm{l}}(t)$: Speed of the leading vehicle in time t
- $V_{\mathrm{f}}(t)$: Speed of the following vehicle in time t
- g(t): Gap to the leading vehicle in time t
- τ: Driver's reaction time (usually 1 second)
- b: Deceleration function

Typically, the speed of a following vehicle is lower than the safe speed and the maximum speed permitted on the road. This speed is often referred to as the "desired" speed and can be determined using the following equation.

$$V_{\mathrm{des}}(t) = min[V_{\mathrm{max}}, v(t) + a(V)\triangle t, V_{\mathrm{safe}}(t)] \tag{6}$$

where V_{max} is the maximum speed allowed on the road in (m/s), a is the acceleration of the vehicle (m/s^2) and $\triangle t$ is the step duration of simulation.

A. Need for a Comprehensive Traffic Simulation Model in Indian Context

A realistic model of driving or driver behaviour must be a comprehensive model which models both lateral control (steering control) and longitudinal control (speed control) under the impact of both roadway and traffic features. According to this aspect of control, microscopic models can be categorised into (i) longitudinal control models, (ii) lateral control models, and (iii) comprehensive models discussed in [7].

B. Calibration of Car-following model for Indian traffic conditions

The development of car-following models for Indian traffic conditions involved modifying the General Motors (GM) Model and Hidas Model, which are standard car-following models [2]. These modifications were made by calibrating the parameters using data collected from both urban and non-urban corridors. Comparing the RMSE and MAE values between the estimated and observed data indicates that the developed car-following models demonstrate a reasonable level of accuracy in estimating the accelerations of the following vehicles.

This paper contributes to the development of a realistic car-following model specifically designed for Indian traffic conditions. The Hidas model shows promising results with relatively low errors, indicating its capability to predict driver behaviour, although it may not be well-suited for Indian conditions. This model enables a better understanding of individual driver behaviour, leading to enhanced accuracy in predicting behaviour and facilitating the evaluation of appropriate transport policies.

III. PROBLEM DESCRIPTION

Mixed-mode traffic encompasses a wide range of vehicles and scenarios, from cars, trucks, and motorcycles to urban driving, highway travel, and weather-affected conditions. This complexity poses significant challenges in transportation engineering. Research gaps exist in understanding mixed-mode traffic, especially in developing countries. In this paper, we aim to address this gap by systematically analyzing and optimizing mixed-mode traffic using traffic simulators. It focuses on effectively modeling and simulating the multifaceted dynamics and interactions among various transportation modes. We can refer figure 1 provides a system representation of input data for the traffic simulator, emphasizing the retrieval of macroscopic traffic parameters.

Our research primarily focuses on macroscopic parameters, where the dynamics of individual vehicles are not considered. Instead, we analyze quantities with macroscopic meaning, such as vehicle density $\rho(x,t)$ and average velocity $v(x,t)$, which are both functions of space and time. These quantities are obtained by averaging over a region of sufficiently large spatial extent. In this context, we examine the parameters at

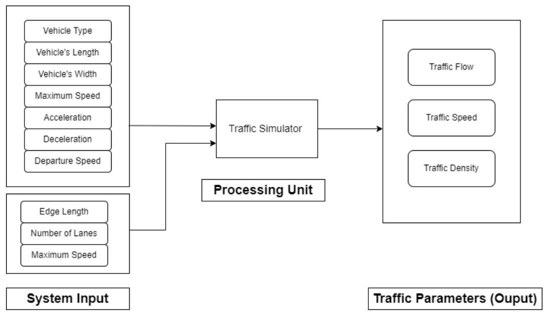


Fig. 1. System Representation

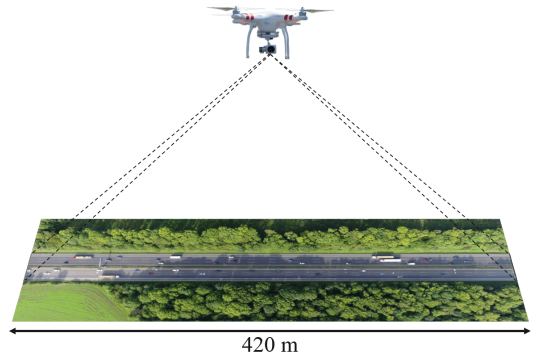


Fig. 2. Recording Setup on a Road Section with a Length of 420m.

a microscopic level, focusing on individual vehicle speed and acceleration. However, for our experiment, we aggregate these values to derive mean speed, traffic flow, and density through temporal and spatial averaging.

Our research endeavor seeks to address the following primary research questions:

1) How can the traffic simulator be suitably customized and configured to accurately represent the intricacies of mixed-mode traffic, encompassing different types of vehicles?
2) Which associated parameters are most appropriate for mixed-mode traffic within the simulation tool, enabling the faithful representation of realistic interactions and movement patterns?
3) How can the macroscopic parameters such as traffic flow, traffic speed, and traffic density be comprehensively evaluated and optimized within the context of mixed-mode traffic scenarios?

In this research, the Root Mean Square Error (RMSE) has been adopted as the evaluation metric for assessing the performance of the mixed-mode traffic model.

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{7}$$

A lower RMSE value indicates a better fit of the model and higher RMSE value suggests a larger average discrepancy between the predicted and observed values.

Our research also assumes that the road conditions are normal, meaning that they do not include any instances of heavy rain, snow, fog, icy roads, or similar adverse weather conditions and the traffic data offers accurate information regarding traffic parameters.

IV. TRAFFIC DATA SET: EXPLORATION AND ANALYSIS

In our study, we acquired the HighD dataset [4], a novel collection of naturalistic vehicle trajectories obtained from German highways. This dataset encompasses both cars and trucks. Additionally, our research also incorporated the Chennai dataset [3], which features a diverse range of vehicles including bikes, rickshaws, cars, and heavy vehicles, recorded in Chennai, India. This combination of datasets allowed us to comprehensively analyze and explore various aspects of mixed-mode traffic.

In HighD dataset, authors have used camera-equipped drones to measure every vehicle's position and movements from an aerial perspective for scenario-based validation. So, a drone was hovering next to German highways and the recordings cover a road segment of about 420 m as displayed in Figure 2. HighD data consists of three CSV files containing information about the site, the vehicles and the extracted trajectories.

Turning our attention to the Chennai dataset, it comprises video footage gathered from the bustling urban thoroughfare known as Maraimalai Adigalar Bridge in Saidapet, Chennai, India. This road boasts six lanes and is engineered to segregate and manage vehicular traffic efficiently. The chosen section of the road is situated on a bridge, ensuring a consistent road layout and eliminating potential influences such as nearby intersections, parked vehicles, or bus stops that could impact driver behavior.

The dataset obtained from the study comprises 3005 trajectories of vehicles. These trajectories were recorded at a resolution of 0.5 seconds, resulting in a total of 111,629 observations. The collected data has 26.6% passenger cars, 56.4% motorcycles, 12.2% of auto-rickshaws and 4.8% heavy vehicles.

V. EXPERIMENTS AND RESULTS

In order to tackle the intricacies and obstacles within the field of transportation, researchers have increasingly embraced sophisticated simulation tools. These tools can precisely replicate and evaluate diverse traffic variables while gauging the repercussions of various transportation strategies. In this context, SUMO (Simulation of Urban Mobility) Eclipse [6] emerges as a powerful software tool that offers a comprehensive platform for traffic simulation and analysis.

In our research, we have employed version 1.14 of the SUMO as our primary tool for traffic simulation and analysis. Additionally, for the creation and editing of the network file, we have utilized version 1.14 of NETEDIT [1]. Similarly,

[1]https://sumo.dlr.de/docs/Netedit/index.html

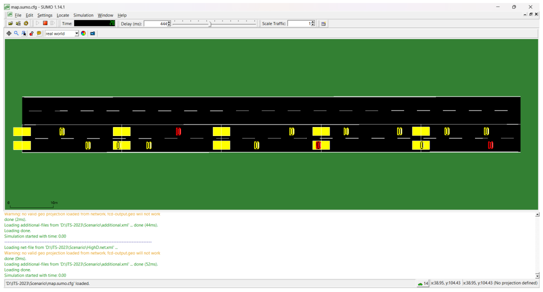


Fig. 3. HighD Road Simulation Snapshot

Parameter	Unit	RMSE	% RMSE	Mean Error
Flow	Total Flow @ 100m	2.15	7.51	0.23
	Car Flow @ 100m	1.82	8.18	0.17
	Truck Flow @ 100m	0.82	13.48	0.06
	Total Flow @ 400m	1.55	5.41	0.09
	Car Flow @ 400m	1.44	6.44	0.08
	Truck Flow @ 400m	0.71	11.49	0.01
Density	Total Density	5.83	20.76	4.88
	Density of Car	4.47	20.32	3.50
	Density of Truck	1.90	30.91	0.91
Speed	Total Speed	5.21	15.95	5.14
	Speed of Car	5.00	14.31	4.88
	Speed of Truck	8.69	35.85	6.83

TABLE I
AGGREGATE ERROR IN ALL TRACKS-V1

Parameter	Unit	RMSE	% RMSE	Mean Error
Flow	Total Flow @ 100m	3.07	10.59	0.13
	Car Flow @ 100m	2.61	11.52	0.10
	Truck Flow @ 100m	1.11	18.13	0.03
	Total Flow @ 400m	3.48	12.06	0.09
	Car Flow @ 400m	3.01	13.32	0.07
	Truck Flow @ 400m	1.14	18.98	0.08
Density	Total Density	7.43	26.36	6.09
	Density of Car	5.53	25.11	4.25
	Density of Truck	2.50	40.71	1.81
Speed	Total Speed	1.85	5.70	-1.25
	Speed of Car	2.16	6.20	-1.34
	Speed of Truck	1.46	6.05	0.80

TABLE II
AGGREGATE ERROR IN ALL TRACKS-V2

we write route file and information about loop detectors in additional file.

Here, we have analyzed the dataset for tracks: 1, 3, 5, and 9. The road built in SUMO, which is shown in figure 3, is a freeway that consists of two lanes in each direction. The total length of the road is 420 meters. The figure also indicates car-following simulation models of cars and trucks, represented by yellow and red symbols, respectively.

In this study, we assess traffic flow, traffic density, and traffic speed. Our analysis involves 60-second intervals with a 5-second displacement between each interval. For instance, we consider time segments like (0-60 seconds), (5-65 seconds), and so forth. We examine a road segment with a length of 420 meters. To calculate traffic flow, we observe vehicle counts at points located at D=100 meters, D=200 meters, D=300 meters, and D=400 meters during one-minute intervals.

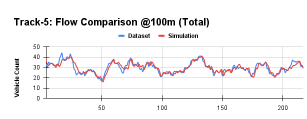
We have written python scripts to export SUMO's simulation output data (fcd.xml) into a compatible CSV format, containing crucial information like vehicle trajectories and speeds. All the required python files can be accessed through Code Repository.

Upon conducting the initial SUMO simulation (called version-V1) using its default parameters for the given HighD dataset, we observe distinct aggregate results for tracks 1, 3, 5, and 9. Throughout this simulation, SUMO utilizes the default acceleration values of 2.6 m/s² for cars and 1.3 m/s² for trucks. However, this default configuration leads to a substantial deviation in traffic speeds. The above table I illustrates these findings, revealing notable disparities in traffic density and speed when compared to the dataset, despite achieving a reasonable traffic flow alignment.

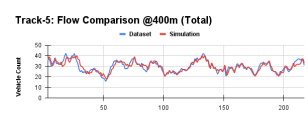
By rerunning the simulation (called version-V2) using the precise acceleration values specified in the dataset (1.13 m/s² for cars and 0.25 m/s² for trucks), we achieve traffic speed that closely aligns with the dataset. However, notable disparities arise in traffic flow and density, as depicted in the table II above. These variations in flow and density appear from the presence of vehicles positioned at intermediate locations along the 0m to 400m road stretch, thereby altering the vehicle count and density measurements.

Now, to mitigate the influence of initial conditions, we eliminate vehicles positioned within the 0 m to 400 m range on the road stretch. This ensures an accurate count of vehicles traversing the entire road segment. Subsequently, we rerun the SUMO simulation, incorporating the dataset's specified acceleration values (1.13 m/s² for cars and 0.25 m/s² for trucks).

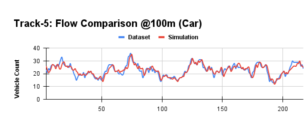
In this paper, we have included the graphical results of track



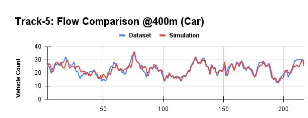
(a) RMSE of Total Vehicles'Flow at 100m: 8.14 with Mean Error of -0.05



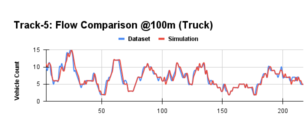
(b) RMSE of Total Vehicles'Flow at 400m: 8.07 with Mean Error of -0.06



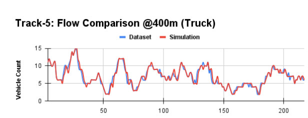
(c) RMSE of Total Cars'Flow at 100m: 9.16 with Mean Error of -0.06



(d) RMSE of Total Cars'Flow at 400m: 9.33 with Mean Error of -0.06

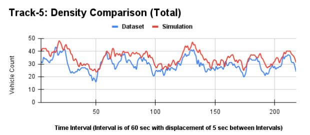


(e) RMSE of Total Trucks'Flow at 100m: 11.31 with Mean Error of 0.01

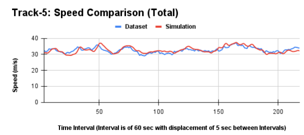


(f) RMSE of Total Trucks'Flow at 400m: 10.38 with Mean Error of 0

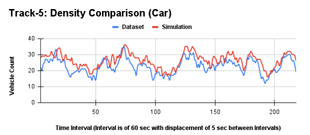
Fig. 4. Flow Results of Track-5



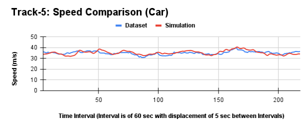
(a) RMSE of Total Density: 20.91 with Mean Error of 5.20



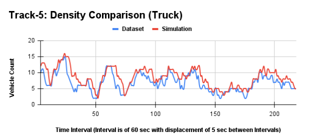
(b) RMSE of Total Speed: 3.85 with Mean Error of 0.13



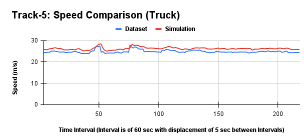
(c) RMSE of Car Density: 20.16 with Mean Error of 3.62



(d) RMSE of Car Speed: 4.55 with Mean Error of 0.29



(e) RMSE of Truck Density: 32.73 with Mean Error of 1.58



(f) RMSE of Truck Speed: 5.79 with Mean Error of 1.38

Fig. 5. Speed and Density Results of Track-5

5. Here, all the results are presented as percentages of RMSE. Upon analyzing the graphs shown in figure 4, it becomes evident that the traffic flow at both 100 meters and 400 meters exhibits a close resemblance to the simulation model. This suggests that the simulation model is effectively capturing the dynamics of traffic flow in the given scenarios, leading to reliable and accurate results.

Based on the presented findings, it is evident from figure 5 that traffic density does not exhibit a strong correlation with the dataset and yields a significant level of error, particularly for trucks. However, it is noteworthy that traffic speed demonstrates a close match with the dataset. These results suggest that the simulation model effectively captures the dynamics of traffic speed but faces challenges in accurately representing traffic density, especially for heavy vehicles.

The below table IV demonstrates aggregate results also (called version-V3) of all tracks: 1, 3, 5 and 9 where we see a strong correspondence between the simulated and dataset values for traffic flow and speed. However, a notable mismatch is evident in traffic density, despite our efforts to tune the acceleration values according to the dataset. Density calculations rely on cumulative measurements of vehicle positions over a given space. Errors in individual vehicle behavior and position measurements can accumulate and significantly impact the accuracy of speed and density predictions. Where as, flow is less affected by these cumulative errors because it simply counts the number of vehicles passing a point. Further investigation is required to gain deeper insights into the underlying causes of this mismatch.

Now, for Chennai data-set, we have configured simulation parameters including time step, inputs and outputs. We have also imported the trajectory data into SUMO, associating

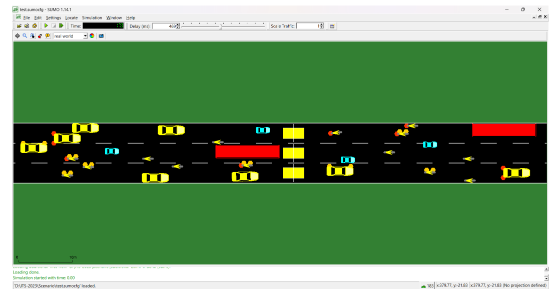


Fig. 6. Chennai Road Simulation Snapshot

Vehicle Type	Mean Flow (veh/hr)	SUMO Flow (veh/hr)	% of Error
Motorcycle	3390	3242	4.37
Car	1600	1540	3.75
Auto-Rickshaw	732	734	-0.27
Heavy Vehicles	288	284	1.39
All types	6010	5800	3.49

TABLE III
AGGREGATE FLOW ANALYSIS

each trajectory with the corresponding vehicle type. Now, to generate the scenario for this data set, we have used the Sub-lane model of SUMO. In this model, the road network's standard lanes are subdivided into smaller sub-lanes, each having a minimum width determined by the specified resolution (–lateral-resolution) provided in sumo.cfg file. Vehicles are assigned to one or multiple sub-lanes, and car-following calculations are conducted for all vehicles that are being followed on at least one sub-lane. We can refer for further details about the sub-lane model. [2]

The road built in SUMO, which is shown in above figure 6, is a bridge that consists of three lanes. In our simulation, the road spans a total length of 735 meters. To ensure accurate observations, we allocated the initial 245 meters as a warm-up space before starting data collection. Loop detectors were strategically positioned at the 370-meter mark, to capture vehicle counts. The simulation was run for a duration of 5400 seconds, with observations focused specifically on the period from 1800 to 3600 seconds, thereby excluding any potential noise data from the experiment. The diagram 6 showcases distinct car-following simulation models for various vehicle types, including mopeds (light yellow), rickshaws (purple), cars (yellow), and buses (red).

Upon conducting the SUMO simulation, we observe a remarkable correspondence between the simulated traffic flow (vehicles/hr) and the dataset. The table III below showcases the percentage of error for traffic flow between the dataset and simulation results. Notably, we observe a mere 3.49% error in traffic flow across all vehicle types, with 4.37% for motorcycles, 3.75% for cars, and 1.39% for heavy vehicles.

The table V above summarizes the percentage of error in traffic density (veh/km/lane) between the dataset and simulation results. The simulation results show a substantial 35.77%

[2]https://sumo.dlr.de/docs/Simulation/SublaneModel.html

Parameter	Unit	RMSE	% RMSE	Mean Error
Flow	Total Flow @ 100m	2.36	8.28	-0.03
	Car Flow @ 100m	2.14	9.59	-0.03
	Truck Flow @ 100m	0.73	11.88	-0.01
	Total Flow @ 400m	2.64	9.28	-0.03
	Car Flow @ 400m	2.37	10.65	-0.02
	Truck Flow @ 400m	0.69	11.34	-0.01
Density	Total Density	6.30	22.46	3.74
	Density of Car	4.83	22.03	2.61
	Density of Truck	2.02	32.81	1.13
Speed	Total Speed	1.73	5.34	-0.82
	Speed of Car	1.96	5.64	-0.78
	Speed of Truck	1.47	6.08	0.49

TABLE IV
AGGREGATE ERROR IN ALL TRACKS-V3

Vehicle Type	Density (veh/km/lane)	SUMO Density (veh/km/lane)	% of Error
Motorcycle	49.34	31.48	36.20
Car	23.46	15.6	33.50
Auto-Rickshaw	13.24	7.8	41.09
Heavy Vehicles	4.78	3.45	27.82
All types	90.81	58.33	35.77

TABLE V
AGGREGATE DENSITY ANALYSIS

error in density across all vehicle types, with motorcycles and cars exhibiting errors of 36.20% and 33.50%, respectively. Heavy vehicles have a lower error of 27.82% in density, while rickshaws show a higher error of 41.09%.

Vehicle Type	Speed (m/s)	SUMO Speed (m/s)	% of Error
Motorcycle	6.01	7.22	20.13
Car	6.13	7	14.19
Auto-Rickshaw	5.06	6.28	24.11
Heavy Vehicles	5.64	6.59	6.84
All types	5.88	7	19.05

TABLE VI
AGGREGATE SPEED ANALYSIS

Table VI presents the percentage of error for traffic speed (m/s) between the dataset and simulation results. Notably, there is a substantial disparity between the simulation and actual dataset when examining the speed values.

VI. CONCLUSION AND FUTURE WORK

Our simulations investigated various factors influencing system performance, and we fine-tuned traffic parameters to minimize the error between simulation and real-world data. Notably, our results demonstrated the effectiveness of SUMO in modeling mixed-mode traffic, closely replicating the HighD dataset with a 10% root mean square error (RMSE) and minimal mean error of -0.03. However, disparities were observed in traffic density, with RMSE percentages of 22.46% for all vehicle types, 22.03% for cars, and 32.81% for trucks, along with a substantial mean error of 3.74. Conversely, the simulation closely approximated the dataset in terms of traffic speed, with RMSE percentages of 5.34% for all vehicle types, 5.64% for cars, and 6.08% for trucks, and a small mean error of -0.82, highlighting the potential of SUMO for modeling mixed-mode traffic.

Similarly, our simulation of the Chennai dataset demonstrated a high level of consistency in terms of traffic flow, with a minimal 3.49% error rate across all vehicles. However, there were notable disparities in traffic speed, showing a 19.05% error rate across all vehicles, and significant deviations in traffic density, exhibiting a 35.7% error rate across all vehicles.

In the simulation setup of SUMO for HighD and Chennai scenarios, car-following parameters were manually tuned, but certain macroscopic parameters like traffic density did not align with the dataset. This suggests the potential use of machine learning models for parameter prediction to enhance simulation accuracy. This work is a proof of concept for creating synthetic data in the context of heterogeneous and laneless environments. Our future aim is to implement machine learning models to automate parameter calibration, providing substantial time and resource savings. Utilizing machine learning models will be advantageous for recognizing trends and predicting system behavior in diverse traffic conditions.

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