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Measurement and analysis of heterogeneous road transport parameters using Smart Traffic Analyzer and SUMO Simulator:An experimental approach

Santhiya Ravindran, Gurukarthik Babu Balachandran *, Prince Winston David

Department of Electrical and Electronics Engineering, Kamaraj College of Engineering and Technology, K.Vellakulam, Madurai, TamilNadu, India, 625701

A R T I C L E I N F O

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A B S T R A C T

The main objective of research work is to study the characteristics of heterogeneous road transport environment & compare its dynamic parameters with the performance metrics measurement in terms of error rate & accuracy for vehicle count and classification using Smart Traffic Analyzer (STA) and SUMO Traffic Simulator. SUMO GUI is a simple tool for microscopic traffic simulation and helps to obtain vehicle dynamic parameters in the easiest way. Experimental research is also carried out by capturing live traffic video at study area of four way intersection road and analyzed through STA. The outcome results from SUMO and STA explicit overall accuracy of 96.63 %, and 95.62 % for vehicle count with the error rate of 3.35% & 4.37%. Similarly for vehicle classification, it provides the overall accuracy of 97.21% and 83.01% with the error rate of 2.78% & 16.97% respectively.

1. Introduction

Intelligent Transportation Systems (ITS) is collection of multiple applications which uses smart information and communication technologies which provide quality services to the all transport users. With the support of recent development in Artificial Intelligence (AI), Communication, Machine Leaning (ML) and Internet technologies, ITS helps to sort out transport related issues like traffic control, congestion [50]control resource management, disaster management and air pollution[60]. Also ITS consists of various advanced transport management system which includes Advanced Traveler Information System (ATIS), Advanced Traffic Management System (ATMS), Advanced Public Transportation System (APTS), Emergency Management System (EMS). Still lot of endless effort is needed for the enrichment of ITS applications [17]. Limitations of ITS covers high maintenance cost, difficulty in traffic data collection, hard to handle mixed traffic and high equipment cost[3]. In the context of traffic safety, as per the statistical report of Ministry of Road Transport and Highways (MORTH), various steps are accounted to create public awareness through workshops, awareness camp and training activities to reduce the road accidents due to type of roads, type of vehicle collision, type of road users, type of vehicles used, road rules violations, type of license, weather condition, road environment, road junctions, vehicle conditions, overloading and age limits [34]. In practical, road traffic (D. wei [59]is heterogeneous rather than homogeneous traffic. It is significant to analyze the road transport network under dynamic traffic conditions to rectify the traffic safety related problems[62]. Macroscopic, microscopic, mesoscopic and sub-microscopic are the different traffic models[9]represented for traffic simulation. Also there are more number of traffic simulation tools are available to replicate the microscopic traffic models. Moreover SUMO is open source and easily accessible & understandable tool to design microscopic and heterogeneous traffic models[27]. SUMO suite 1.13.0 version is preferred for carried out simulation research work. Similarly Smart Traffic Analyzer (STA) 20.0.0 is chosen for doing experimental research. It works based on AI and video processing. STA supports for the traffic analysis and provide real time vehicle classification with count and average vehicle speed & average traffic volume.

1.1. Significance of the research study

In addition to literature survey about related research studies, some facts and figures are investigated to explore the current scenario about utilization of motorized vehicle and population density road accident distribution in India. The country which has the highest population is India and naturally it leads to increase the number of road transports & its utilization. As per the statistics, Fig. 1 is evident that, even though the

* Corresponding author.
E-mail addresses: santhiya1912@gmail.com (S. Ravindran), mspsbguru@gmail.com (G. Babu Balachandran), dpwtce@gmail.com (P. Winston David).

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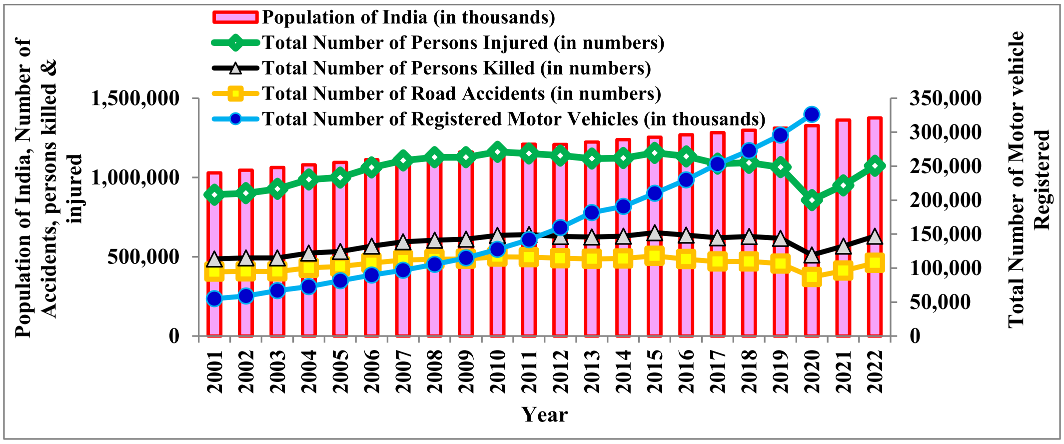


Fig. 1. History of road accident distribution in India with population density and motor vehicle registration (2001 to 2022) (Ministry of Road Transport & Highways, 2022).

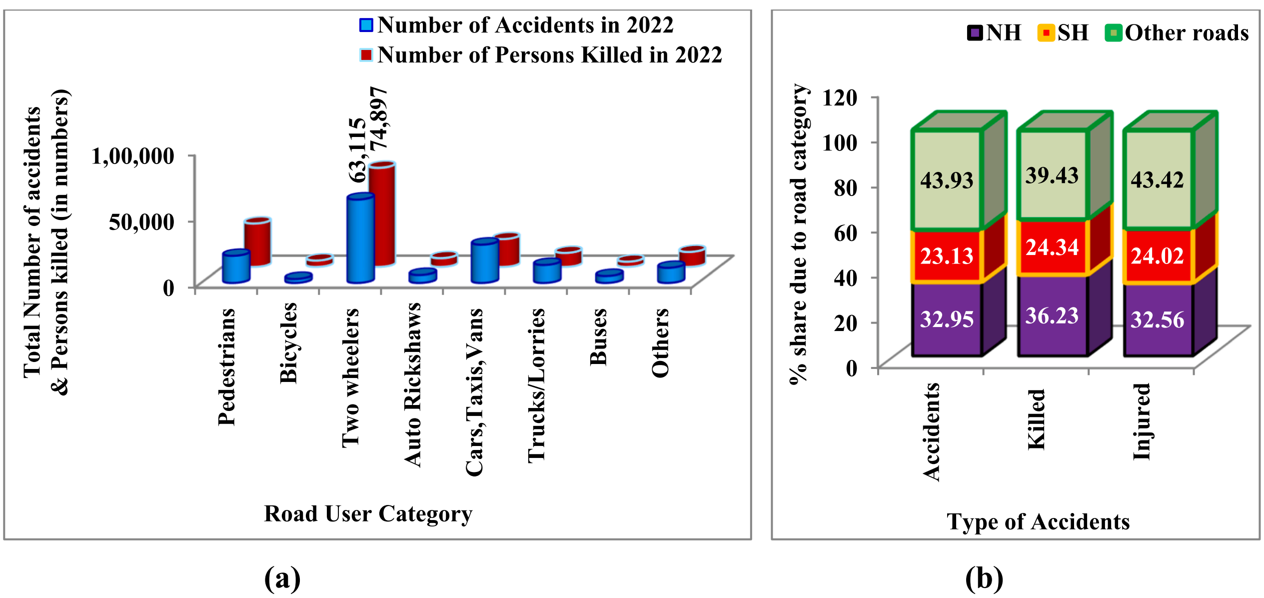


Fig. 2. Road accident distribution in India for the year of 2022 due to road user category and road category.

substantial effort is taken by government and road safety authorities, for the last decade, road accidents in india continuously increased in exponential manner except the covid impacted year of 2020 due to less road traffic during the lock down period and it is necessary and important to identify the most influenced road transport factors which cause the road accidents under dynamic road traffic environment.

Fig. 2(a) and Fig. 2(b) denotes road accident distribution in India due to road user category and road type which reveals that two wheeler users share the highest percentage in road accidents. Similarly, other roads cause more number of accidents with high fatal accidents and injury than National Highway (NH) & State Highway (SH). These statistics are evident that high population, high utilization of motorizsed vehicle leads heavy traffic in crowded area. With this motivation, it is most significant to analyze the heterogeneous road traffic parameters and its behavior on road to minimize the road accidents further.

1.2. Contributions of the research study

The main target of this research study is to investigate the characteristics behavior of heterogeneous road traffic parameters under dynamic traffic environment using SUMO traffic simulator and live traffic monitoring tool of STA and to compare the performance parameters in measuring traffic flow, vehicle speed, trip information, vehicle count and other related information to a vehicle. Also To evaluate the accuracy & error rate for vehicle count & classification in various heterogeneous traffic flow conditions. This study can be supported for strengthening 5E's (Education, Enforcement, Emergency care, Engineering and Encouragement) initiative model for road safety which is initiated of [32].

The primary contributions of this work are highlighted here:

- Live map data of study field along with road traffic environment is obtained using Open street map (OSM) web wizard for simulation purpose.
- Fixed Mini Bullet IP camera is used to capture the live recording of per day traffic flow in the same location preferred for simulation study.
- Collected map data are processed and analyzed using SUMO microscopic traffic simulator under various traffic flow conditions including various road traffic dynamic parameters.
- Also vehicle related information from Captured Live traffic flow video is extracted using STA.

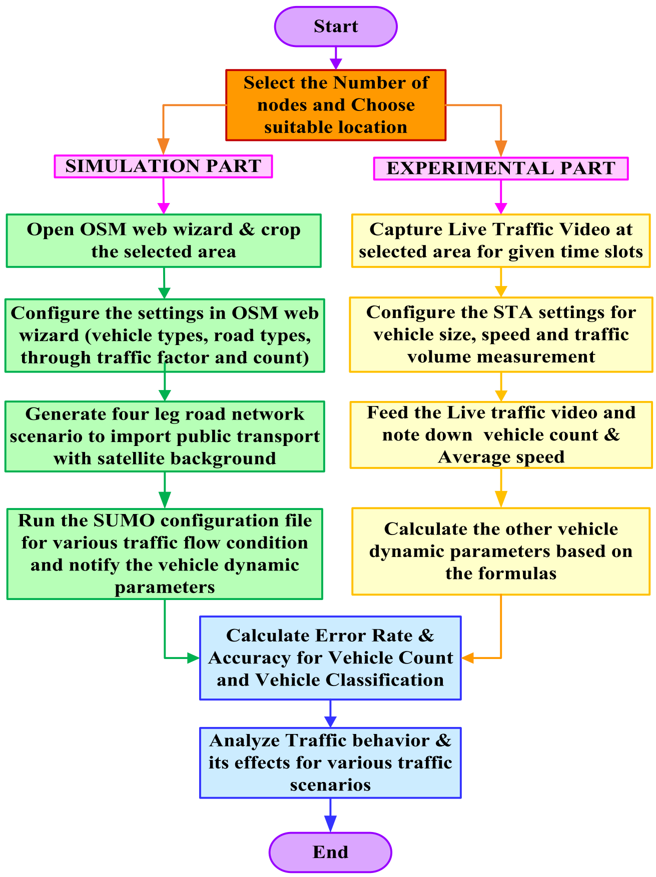


Fig. 3. Process Work Flow.

- Along with Pedestrian, Dynamic traffic environment with Bus, Car, Motor cycle, Bi-cycle and Truck are considered for analysis purpose.
- Various road transport parameters measured from SUMO and STA are compared and additionally, Vehicle count and Vehicle Classification is performed using both the tools in terms of performance metric of accuracy and error rate.
- Over all, the adopted methodology and outcome results will be helpful for supporting the road safety authorities for effective traffic management.

Fig. 3 shows overall process work flow of the research work. Section 2 describes literature review about selected research work. Section 3 discussed the materials and methods used meet the research objectives in terms of methodology adopted, geometric design of study location, modeling of real time road transport network scenario using SUMO and STA with its configuration settings. Section 4 illustrates the simulation and experimental research works carried out using SUMO & STA. Section 5 deals with results and discussion about comparison of simulation & experimental research and followed by conclusions are described in Section 6. Finally, limitations & future recommendations are discussed in Section 7.

2. Related work

2.1. Literature survey on ITS and its applications

ITS technologies and its broad applications (N. H. T. [37,38] helps to reduce the various transportation related issues. Different aspects of ITS applications in the area of metropolitan deployments like Transit Management System, Incident Management System, Emergency Management System, Traveller Information Systems etc., are discussed in [41]. With the help of VANET routing protocols called Optimized Link State Routing (OLSR) and Ad Hoc On-demand Distance Vector Routing (AODV), scenarios for traffic congestion, collision detection, collision avoidance, overtake, emergency are simulated using C++ based simulator and performance metrics in terms of packet delivery ration and average delay are projected to improve quality of the traffic management system[45]. Huge amount of traffic information are retrieved time to time for providing traffic safety, routing tips to the user. Direct Storage of heavy data in block chain database is not a good one. It is important to reduce the dimensionality of data to get the required information quickly without delay. To achieve this, principle compound analysis, non-negative matrix factorization and linear discriminant analysis on road traffic data are performed and error rate is compared. Principle compound analysis method gives less error rate of 32 % compared to other techniques[5].GPU and Reinforcement based learning model support and provides high scalability & security for an ITS [8].Traffic flow[13]prediction plays an important role in improving road safety. RNN-LF based algorithm is suitable for traffic flow prediction from multiple sources[7]. Convolutional neural network [40]based traffic flow prediction model is designed using time space diagram. For assessing the effectiveness of the proposed CNN approach three non-parametric models of support vector regression (SVR), multilayer perceptron (MLP), and autoregressive integrated moving average (ARIMA) are used. ARIMA shows better performance than SVM & MLP for predicting traffic states[24]. However varying spatiotemporal graph-based convolution model also shows better performance for traffic flow prediction with reduced error than other convolutional methods[56]. Overview of sensor technologies, AI based algorithms to avoid vehicle collisions are outlined and also various challenges faced in maintaining vehicle information safety are discussed to sustain data confidentiality and integrity [18].Vehicle dynamic [54] behavior like operating speed, acceleration and deceleration & its relationship are analyzed experimentally using video −VBOX instrument. Under heterogeneous traffic condition [44], probability distribution of parameters analysis is performed at five different cities in india[29]. Optimal pricing scheme for toll gate users is introduced by evaluating the toll road performance using individual gap function vehicle based (IGFV) assignment strategy. Simulation based dynamic traffic data assignment packages embedded with IGFV along with shortest path algorithm to achieve the goal[51]. For a smart transportation, vehicle connectivity and its performance behavior is very important in terms of accuracy and response time. A clustering head based model is proposed to improve the performance of vehicle ad-hoc network using OPNET modeler software. With the help of fuzzy logic, various vehicle characteristics of speed[26], acceleration, distance parameters are combined & tested under two way multilane highway[11].

2.2. Literature survey on SUMO and its applications

Traffic congestion is one of the biggest disadvantages especially in high population area and it causes increased travel time, delay to reach the destination. It highly affects the regularity of emergency vehicles also. It is necessary to design smart traffic[36] management system to reroute the vehicles to reduce traffic congestion in faster way. SUMO based deep neuro fuzzy method is developed to create smart traffic management system [23]. Road weights values are determined by deep neuro fuzzy model and it is proportional to speed. Three different routing algorithms like Dijikstra, A* and CHWrapper are used to obtain optimal route with the help of road weights [2]. Real time road network generation (D. W. [58] and its analysis is difficult under dynamic environment. SUMO [39] is clearly helped to imitate microscopic traffic simulation. Open street map, Netgenerate and Netconvert are the general methods available in SUMO for road network generation. DFROUTER, JTRROUTER, OD2TRIPS, ACTIVITYGEN and DUAROUTER are few packages used for simulating traffic demand generation. The application of SUMO implies greatly to simulate the scenario of vehicle to vehicle communication and vehicle to infrastructure communication [25]. Experimental study is carried out for demonstrating the speed advisory system along with monitoring of CO_2 emissions [36] level in the large scale area. Real vehicle is embedded with SUMO to implement distance and speed based recommendation system. Rerouting technique is also projected based on the driver behavior in the connected vehicle system using smart phone interface [19]. Rerouting of emergency vehicles on the road during the traffic congestion is important to save the life of a person. In order to decrease the travel time and waiting time on road, time based comparative analysis is performed before rerouting and after rerouting. It is noticed that the ravel time of an emergency vehicle is reduced reasonably after rerouting [30]. Random trips are generated using origin–destination matrix packages present in SUMO and performance of six various protocols is notified to simulate VANET environment in terms of packet delivery ratio, packet loss ratio, throughput delay and routing overhead. Performances metrics of Ad hoc on-demand distance vector (AODV) routing protocol provide better results than other routing protocols [10].

2.3. Literature survey on uses of other traffic simulators

A systematic survey is worked out to know about detailed study of various traffic simulators like Aimsun, SUMO, AnyLogic, Polaris, Corsim, Archisim, Heterosim, Transsim, PTV tool kit, Cube/Sugar/urban Engines, DynaMIT, Dracula, INTGRATION, DynusT, Kronos, Mezzo, MovSIM, MITSIM Lab, MATSIM, OmniTrans, Polaris, SATURN, Sidra, Synchro, Transmodeler and urbanism. Genarally, traffic behavior is classified into two methods. First one is Homogeneous traffic which means it follows strict line discipline and there is vehicle structure does not change much more. Second one is Heterogeneous traffic which means it does not follow strict line discipline and different kind of vehicle types are involved in road transportation. USA and Europe adheres homogeneous traffic where as india & Pakistan adheres heterogeneous traffic. A lot of research work is performed for homogenious traffic rather than heterogeneous. SUMO is one of the traffic simulators to model heterogeneous traffic. Selection of suitable traffic simulators for particular application which is required to know the features of each simulators [53], (J. [37,38]. Various traffic simulators and its features are compared based on driver behavior and vehicle behavior under car following scenario[31]. Traffic simulation software are compared based on a set of criteria which include simulation model, software category, visualization, type of system, infrastructure, type of vehicles, pedestrians, scope area, detectors and geographic information system. SUMO, TRANSSIM, MATSIM and MATSIM LAB are open source traffic simulators[43,16].

2.4. Literature survey on traffic monitoring system

Vision based traffic monitoring is biggest challenges for dynamic environment. LIDAR, RADAR and cameras are usually used to detect the objects on road side. Camera based traffic monitoring system is widely used method for analyzing live traffic information. Placing a camera on road side may be at center or corner of road intersection. The process of vision based traffic monitoring system is follows as vehicle detection, vehicle tracking, vehicle classification, behavior understanding, risk assessment and decision making. video based traffic analysis takes more computational time, need more care for environmental changes and require preprocessing to use the collected data [15].Sensor technology is the key area of ITS applications. Intrusive and Non-Intrusive sensors and manual counting are the methods for studying about traffic flow characteristics. A new approach is proposed with the complex road structure of two way multi lanes & three U-turns to avoid the limitation of non-intrusive & intrusive sensors by predicting pedestrian behavior under heterogeneous vehicle traffic[4]. Image processing based vehicle detection and classification method is proposed for identifying the truck in the road environment using visual c# programming and obtained the 97 % accuracy for vehicle detection and less than 9 % for vehicle count error [61].

In practical, there are number of difficulties faced during the dynamic traffic data collection to improve the accuracy. Infrared based TIRTL instrument, TRAZER traffic monitoring software and Google distance matrix are the three methods used for effective traffic data extraction. Google distance matrix method is the suitable application for collecting real traffic data than other methods with high accuracy[21]. Vehicle counting [1] from real time traffic through manual process is challenging one. However The effect of traffic density in different time slots are discussed through manual process as well as Picomixer STA. Heavy traffic and more traffic signals [12]leads to increase the travelling time[42]. Real time vehicle tracking and classification from heterogeneous traffic video is done using SVM technique. A new histogram based kernel classifier is used for vehicle classification. Blob tracking & subtraction background model is preferred for vehicle tracking and got the vehicle count accuracy of 84 % for early morning, 90.8 % for morning, 88.9 % for noon and 90.4 % for afternoon [33]. Fuzzy logic approach is proposed for vehicle classification with image processing technique. The average processing time for analyzing the 265 images is 9.388 s & explicit the overall accuracy of 98.87 % [14]. video based non-homogeneous traffic scenes are analyzed to plan the traffic pattern by deriving passenger car unit using continuity equation & density method. For handling homogeneous traffic, 4 lanes divided highways with service lanes is better than 6 lanes divided highways without service lanes [52].

2.5. Findings from literature survey and research gap Identification

In general, research methodology is may be survey based research or technical based research. In related to road transportation, the most of the survey articles are concentrated on role & necessity of ITS and also discussed about ITS limitations and applications to develop smart sustainable transportation system with the support of suitable techniques or tools. The available technical research articles are focused on safety and security of an ITS. A lot of forward steps are moved to lift the ITS infrastructure. But still, more effort is needed to achieve this. The next important limitation of ITS is mixed traffic. Lot of existing research papers is doing analysis with homogeneous traffic rather than heterogeneous due to its complexity in nature. At the same time, simulation helps us to project exact scenario of real time in virtual screen. There is more number of transportation simulating software available like VISSIM, VISUM, AIMSUN & SimTraffic etc. Researcher prefers SUMO[46] traffic simulation tool due to its simplicity, openly available, ability handle heterogeneous traffic and flexibility in use. Similarly, in the part of real time traffic monitoring[28], different applications called TIRTL instrument, Picomixer STA, Traffic vision & TRAZER are used. Vehicle tracking, detection and classification and performance measurements are the kind of processes involved in ITS applications. Smart traffic management system helps to reduce road accidents[47]due to heavy traffic, reduce congestion and also decrease the travelling time. In our research paper, we select Picomixer STA due to its ease of availability. The main purpose of this paper is to analysis the real heterogeneous road transport behavior using SUMO transportation simulation tool and Picomixer STA and to compare the performance metrics measured by

Table 1
Time Slots Consideration and Assumed Traffic Flow.

Traffic Scenarios	Time Slots	Traffic Flow
1	Morning (Around 8.00 am)	High
2	Noon (Around 12.01 pm)	Very High
3	Evening (Around 5.00 pm)	Moderate
4	Night (Around 9.00 pm)	Less Moderate
5	Late Night (Around 11.00 pm)	Low

Table 2
Configuration values for Traffic Demand Generation at selected four leg intersection road.

Parameters	Magnitude (For Simulation)	Magnitude (For Experiment)
Longitude of Selected area	9.580324° N	9.580188° N
Latitude of Selected area	77.953649° E	77.953157° E
Number of Nodes	5	5
Number of Edges	8	8
Tools Used	OSM web wizard	Video camera
RunningTime	5 min	5 min

the both methods in terms of error rate and accuracy for vehicle count and vehicle classification.

3. Materials and methods

3.1. Methodology and assumptions Considered

Live traffic video is captured at selected area for 5 min duration [33] is considered as per the mentioned time slots given in Table 1. Including pedestrian, car, bus, motorcycle, truck, bicycle, auto rickshaw and van are the various vehicles involved in real time traffic and are counted manually. Before starting the research on dynamic traffic analysis, few assumptions are considered for doing simulation and experimental work. In manual method, auto rickshaw is included in car category for counting process. Similarly, manual counting process is also done due to STA has the live traffic vehicle counting panel for heavy vehicles and cars only. Heavy vehicles include bus, truck, mini bus and trailer. In STA, All the motor cycles count is considered in car category. To avoid the effect of this limitation, with reference to manual counting, motorcycle category is excluded from car category but considered for total vehicle in STA. The other assumptions based on environmental fact are weather condition is normal and no rainy. Only moving objects are considered for evaluation process.

3.2. Geometric design

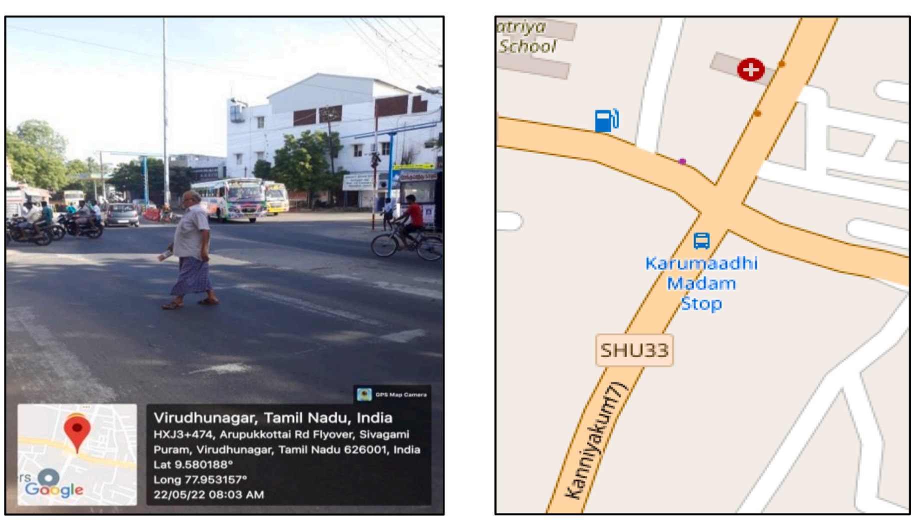
Table 2 represents the road network specification parameters used for simulation and experiment. These values are taken into account as per the information derived from Fig. 5. Four leg intersection roads are considered for creating road network. The selected real time location is Karumaadhi madam, Aruppukottai road, Virudhunagar, Tamilnadu, India which is represented in Fig. 4 and is selected because this place faces traffic congestion during peak traffic hours. Usually heavy traffic is occurred by motorized vehicles (especially bike & auto rickshaw) at the morning & evening due to picking up /dropping the students to school/ college. Additionally van, college buses or public transportation are included in this category. Similarly the influence of heavy vehicles like truck, lorry & emergency vehicles also a major role in creating traffic at the selected study area.

3.3. Modeling of real time road network scenario using OSM web wizard and SUMO GUI

Open Street Map (OSM) database is popular one to extract the real map data and is considered for importing real time traffic data to start the simulation. Open street map is widely adapted method for importing real map. OSM web wizard tool is the simplest one to generate real heterogeneous traffic in simulation environment and various processes involved in creating real road network using OSM web-wizard and SUMO GUI is represented by Fig. 5. It involves the various stages including study area selection, through traffic factor & count settings, road environment parameters settings and other supporting files creation. The required supporting files are 1. map file (.osm format) which contains the information about longitude and latitude values of selected study location through OSM. 2. Node file & Edge file (.nod.xml, edg.xml format) contains the information about the number of nodes and edges based on data in the map file. Edge type informs us how many numbers of lane and type of vehicle in the lane. 3. Net file implies the connectivity of nodes and edges to form the road networking. 4. Trip file defines the random trips of vehicle for a period of time by vehicle id, vehicle speed and destination point.5.Route file defines the end to end routes of each vehicle based on the each vehicle destination point. 6.Sumocfg file combines the effect of route file and net file in order to create real road environment. In OSM web wizard website, we need to specify the study location and other required parameters and entire files are automatically downloaded for simulation with SUMO configuration through generates scenario option and we can modify the necessary parameters like vehicle speed, lane number, simulation time, vehicle type or any other vehicle information.

3.3.1. SUMO Configurations for simulation

SUMO simulator configuration involves various stages of processes



(a) (b)

Fig. 4. Study area-Karumaadhi Madam Stop, for road transport analysis (a) Live screenshot for analysing through STA (b) Area Selection from OSM Web wizard for analysing through SUMO.

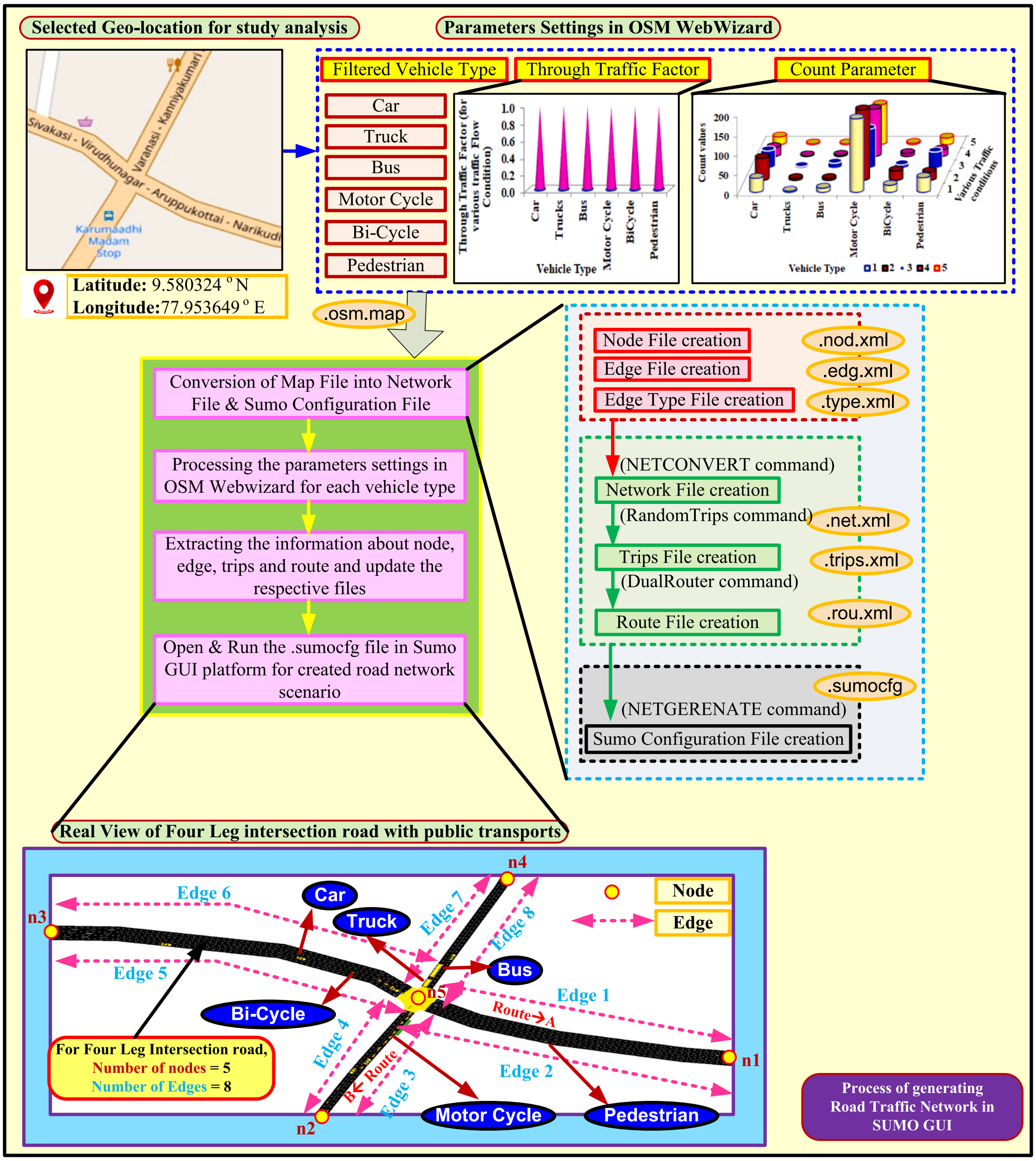


Fig. 5. Process Flow involved in road traffic creation using SUMO GUI and Opens Street Map.

as per the Fig. 5 for generating real road environment. According to the output obtained from the method of manual counting and STA, in

OSM web wizard, for the selected longitude & latitude, traffic through factor and count values are adjusted to create respective net file, trips file & route file and so sumo configuration file is modified in terms of total number of vehicles, vehicle type in each traffic flow condition, pedestrian etc. The sample web code generated for intermediate files while creating the real road environment for the transformation from map data to sumo configuration file for the traffic scenario 5 is given as supplementary file. The number of nodes and edges are assigned for 4 leg intersections is 5 and 8. The delay value is set to 20 ms for starting the simulation. Parameters setting in SUMO simulator made as to produce the same output like STA.

3.4. *Real time traffic monitoring using STA*

Experimental test setup is located close to the selected study area by installing 4Mp (Mega Pixel) fixed mini bullet camera (model No: PT-NC140D3-IUF (D)) at 20feet height at 45^0 angle with respect to pole. The live traffic video was recorded for 5 min duration [33]in the different timings of a whole day around 8.00am, 12.00 noon, 5.00 pm, 9.00 pm and 11.00 pm. Fig. 6 denotes the various kind of steps involved in processing the streamed video using STA.

3.4.1. *STA Configurations for real traffic monitoring*

STA configuration involves enabling the features of STA live monitoring tool for 1.vehicle motion settings either left to right/ right to left/ both. 2. Vehicle size in pixel, 3. Vehicle detection & its sensitivity, 4. Vehicle classification & its sensitivity, 5. Vehicle diversity, 6. Maximum vehicle speed, 7. Traffic volume & 8.Average vehicle speed measurement. The configuration settings considered for this experiment are vehicle motion (both direction), Vehicle size (The maximum width & length –27 x 57 for car, 39 x 89 for minibus/truck and 55 x 163 for bus or trailer), maximum vehicle speed is 80 km/hr and for other parameters default values are taken into account.

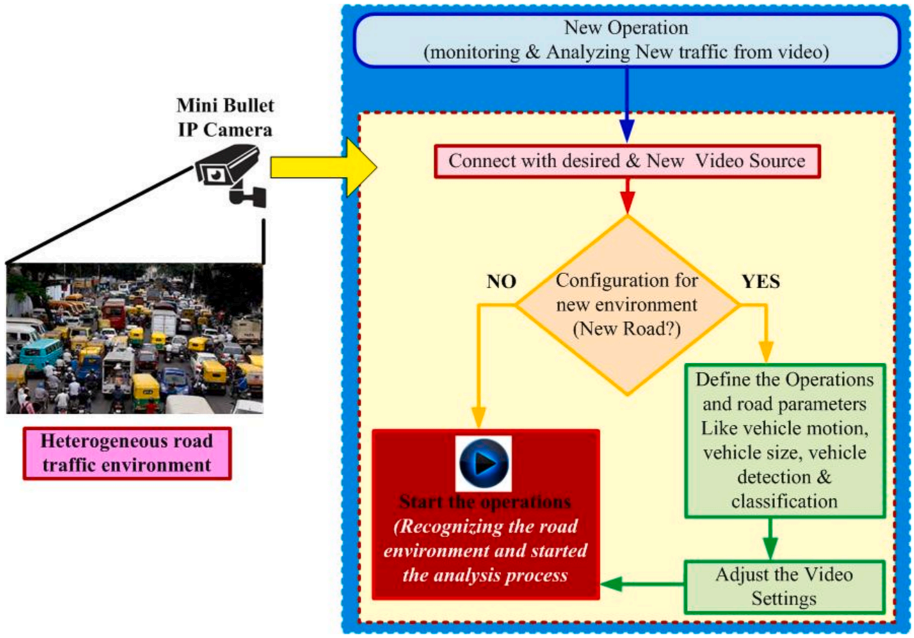


Fig. 6. STA Configuration Flow process.

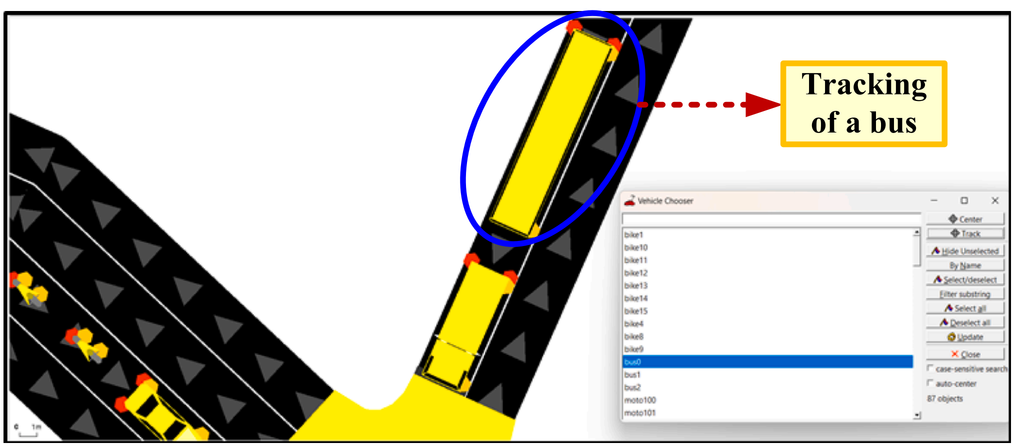


Fig. 7. Tracking of a bus in SUMO simulator for sample.

4. Simulation versus experimental research work

4.1. Simulation research work

SUMO GUI has the application of OSM web wizard and it is the simple way to create real road network. Different vehicle types, road types are included to simulate the road network scenario including public transports with satellite background. SUMO GUI produces the average values of road network parameters which are considered for the analysis & are named as average trip length, average trip duration, average trip speed, average speed, average trip waiting time, average trip time loss, Trip Departure Delay and vehicle count. Table 5 represents the measured output for vehicle count under heterogeneous traffic using SUMO. The simulation is done for 300 s. Tracking of all the vehicles and its related informations are gathered after running the sumo configuration file in SUMO GUI environment.

Fig. 7 denotes screenshots of traknig of a bus from heterogenious road environment through SUMO simulator. Similarly, all the vehicles are tracked dynamically and the results for various dynamic parameters are obtained as per the simulation part of work flow as per the Fig. 3. The following parameters of road transport network like traffic demand, trip length, trip duration, trip departure delay and trip speed are measured basis on the Equations[22,6,48,20],(*Sumo* [49]. Fig. 8 illustrates output of SUMO simulation which contains the study area selection at OSM web wizard and Heterogeneous road transport scenario creation using SUMO under various traffic flow condition.

Traffic Demand is defined as the number of vehicles loaded vehicles in traffic for a period of time. Usually, it is represented in vehicle per hour. In SUMO – OSM web wizard, depends on the through traffic factor and count parameter traffic demand is generated. Through Traffic Factor means how many vehicles that arrive and depart at the boundary of simulation area and its value is set to 1 here. Trip Speed is different from average speed of a vehicle and is varied depends on road condition. Average Trip Waiting Time is defined as the time spent for standing like taking lunch or doing any involuntary work and Average Trip Time Loss is defined as the time loss due to driving lower than desired speed and represented in seconds. It includes the waiting time also. Average Trip Departure Time is defined as the average time taken by the vehicles to wait before started its journey.

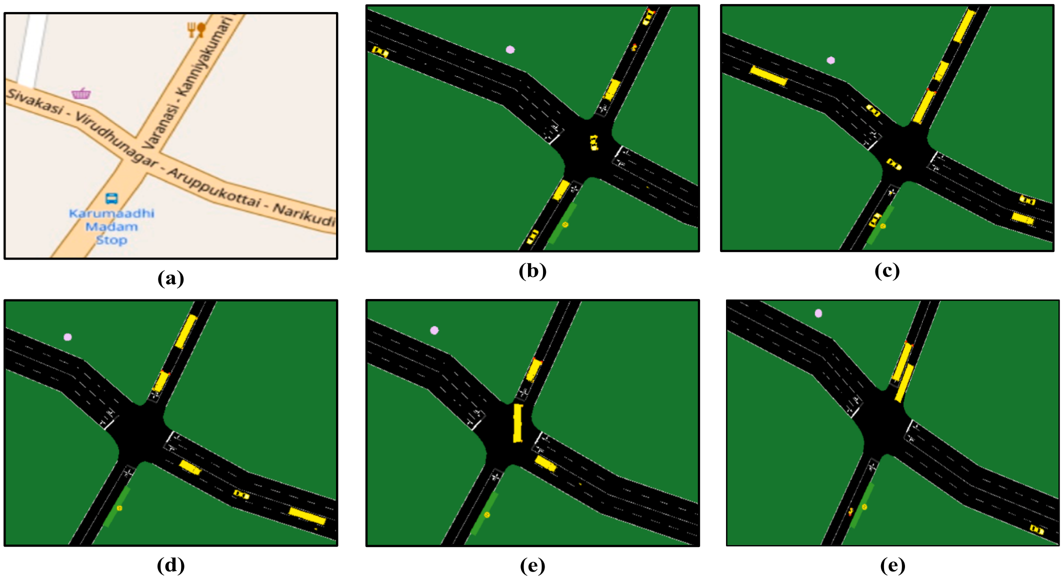


Fig. 8. Heterogeneous road transport scenario creation using SUMO (a) Selected place at OSM Web wizard, (b) Traffic scenario 1, (c) Traffic scenario 2, (d) Traffic scenario 3, (e) Traffic scenario 4 and (f) Traffic scenario 5.

Table 3
Hypothetical values assigned for the road transport parameters (for analyzed through STA).

Traffic Scenarios	Average TripLength (km)	Average Speed of a vehicle (km/hr)	Average Trip Waiting Time(s)	Average Trip TimeLoss (s)	Average Trip Departure Delay (s)
1	0.6	21	6	20	0.5
2	0.6	22	8	22	0.5
3	0.6	23	4	18	0.5
4	0.6	26	2	16	0.45
5	0.6	28	1	14	0.45

Table 4
Vehicle Count for various traffic scenarios (Manual Method).

Traffic Scenarios	Individual Vehicle Count based on the vehicle types						Total Vehicle Count (Manual Method)
	Car	Truck	Bus	Motor Cycle	Bi-cycle	Pedestrians	
1	25	2	7	130	12	25	176
2	39	3	3	125	16	14	186
3	32	3	10	69	6	28	120
4	17	1	2	83	5	11	108
5	14	1	1	70	2	11	88

4.2. Experimental research work

Smart Traffic Analyzer (STA) is one of the easiest traffic monitoring application. It has the facilities for live vehicle detection, live vehicle counting and live traffic monitoring. We can extract the live traffic data of vehicle count and average speed from the recorded live traffic video. At the selected place, live traffic video is recorded for 300 s and used as input to STA in order to extract the traffic information. Hardware implementation is carried out as the steps given in experimental part of Fig. 3. Similar to the simulation environment, the same road network parameters are taken into account for practical approach also. Average trip duration is evaluated using mathematical equation. STA provides only the values for vehicle count and average trip speed and so the other parameters of trip length, average speed of a vehicle, average trip time

Table 5
Estimated vehicle count for various traffic scenarios using SUMO.

Traffic Scenarios	Individual Vehicle Count based on the vehicle types						Total Vehicle Count (SUMO)
	Car	Truck	Bus	Motor Cycle	Bi-cycle	Pedestrians	
1	24	2	7	126	12	25	171
2	38	3	3	121	16	14	181
3	30	3	9	67	6	28	115
4	15	1	2	81	5	11	104
5	13	1	1	68	2	11	85

Table 6
Estimated vehicle count for various traffic scenarios using STA.

Traffic Scenarios	Individual Vehicle Count based on the vehicle types					Total Vehicle Count (STA)
	Car	Truck	Bus	Mini-Bus	Trailer	
1	22	1	6	5	6	170
2	36	2	2	4	9	178
3	26	2	8	5	5	114
4	14	1	2	3	6	103
5	12	1	1	2	2	84

loss, average trip waiting time & trip departure delay are assumed as a hypothetical value depends on the real time situation for continuing the experimental part as per the Table 3. Due to the limitations of STA, manual vehicle counting is also processed and shown in Table 4 and the estimated vehicle count after extracting the information from live traffic video using STA is shown in Table 6. Live tracking of vehicles under heterogeneous road traffic environment at different time slots for detection & classification using STA are represented in Fig. 9. After measured all the road network parameters, by comparing the results of SUMO and STA, performance metrics of accuracy and error rate for the vehicle count & classification is evaluated.

using below terminology.

Accuracy is the quality of a product or instrument. High accuracy means system provides zero error. It is measured from the deviation of percentage error. Error rate is defined as the ratio of deviation between the true value & measured value and true value. The percentage error is

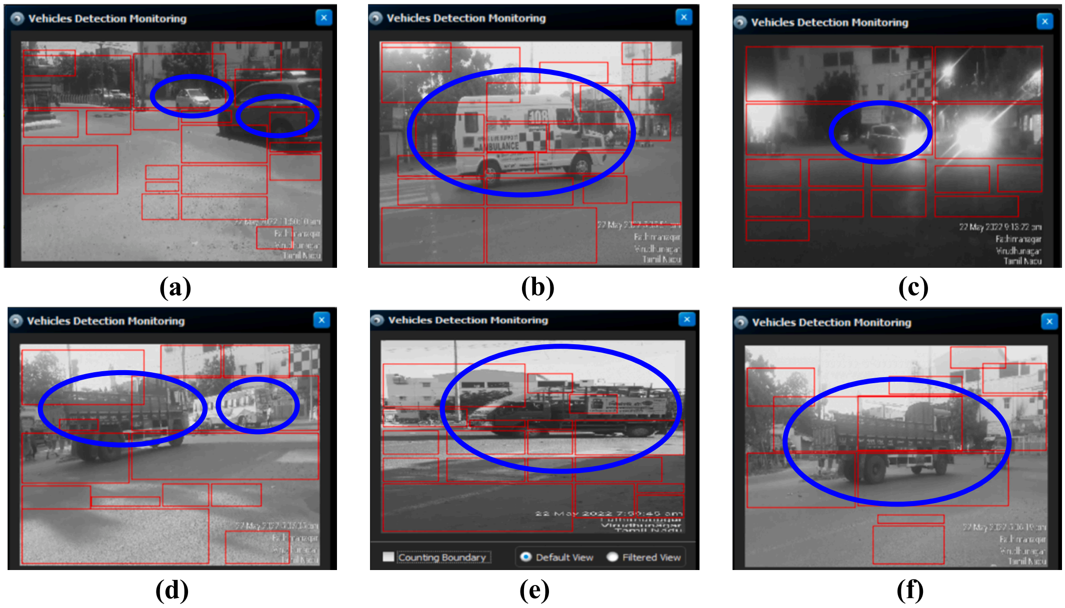


Fig. 9. Sample screenshots for tracking of Vehicle using STA. (a) Tracking of a car, (b) Tracking of an ambulance car (c) Tracking of a car at night time, (d) Tracking of heavy vehicle (Lorry & Bus), (e) Tracking of heavy vehicle (truck) and (f) Tracking of heavy vehicle (Lorry).

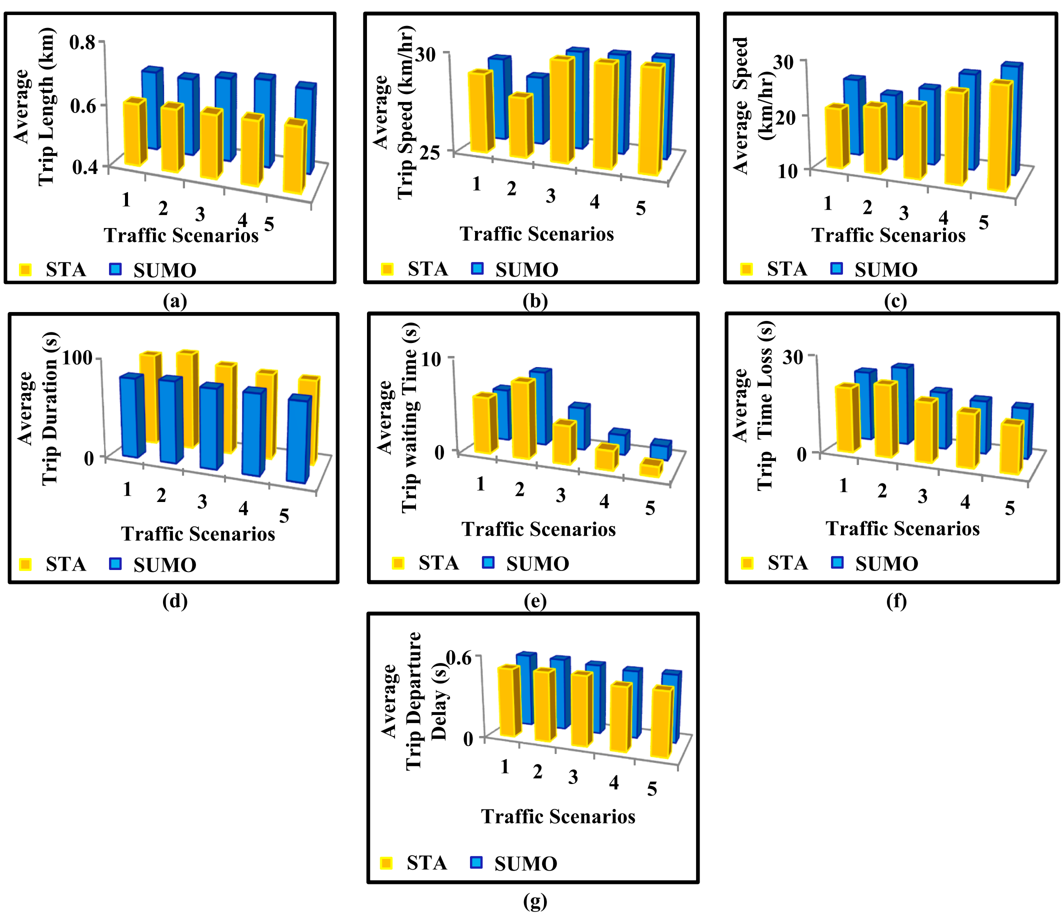


Fig. 10. Road Network parameters Comparison-SUMO versus STA (a) Average Trip Length (b) Average Trip Speed (c) Average Trip Speed (d) Average Trip Duration (e) Average Trip Waiting Time (f) Average Trip Time Loss (g) Average Trip Departure Delay.

Table 7
Accuracy & Error Rate for Vehicle Count-SUMO versus STA.

Traffic Scenarios	Accuracy forVehicle Count in SUMO (%)	Accuracy forVehicle count in STA (%)	Error Rate for Vehicle Count in SUMO (%)	Error Rate for Vehicle count in STA (%)
1	97.15	96.59	2.84	3.40
2	97.31	95.69	2.68	4.30
3	95.83	95	4.16	5
4	96.29	95.37	3.70	4.62
5	96.59	95.45	3.40	4.54

Table 8
Accuracy & Error Rate for Vehicle Classification- SUMO versus STA.

Traffic Scenarios	Vehicle Classification Accuracy in SUMO (%)			Vehicle Classification Accuracy in STA (%)		
	Bus	Truck	Car	Bus	Truck	Car
1	100	100	96	85.71	50	88
2	100	100	97.43	66.66	66.66	92.30
3	90	100	93.75	80	66.66	81.25
4	100	100	88.23	100	100	82.35
5	100	100	92.85	100	100	85.71
Traffic Scenarios	Vehicle Classification Error Rate in SUMO (%)			Vehicle Classification Error Rate in STA (%)		
	Bus	Truck	Car	Bus	Truck	Car
1	0	0	4	14.28	50	12
2	0	0	2.56	33.33	33.33	7.69
3	10	0	6.25	20	33.33	18.75
4	0	0	11.76	0	0	17.64
5	0	0	7.14	0	0	14.28

estimated by below equation (1).

$$\%\,\text{Error rate} = (\text{True value} - \text{Measured value})/(\text{True value})*100 \quad (1).$$

5. Results and discussion

Totally 8 road transport network parameters & 2 performance parameters are measured and compared using SUMO and STA. Fig. 10 shows the results comparison of various road network parameters under the heterogeneous environment obtained from SUMO & STA for 5 different traffic conditions. It reveals the relationship between each term effectively. Average trip length is considered around 0.6 km in all the five scenarios. As we know, the distance to be travelled decides the trip duration and the routes chosen for reaching the destination place & its road characteristics during whole trip time also have great impact on the trip speed, trip waiting time & predicting the average trip duration. Start-up delay by the drivers / passengers due to personal situations and unexpected traffic congestion severely affect the trip time loss & trip departure delay respectively. In traffic flow characterization, speed and travel time is important factor. From the results, we noticed that in morning, the traffic level is high due to school & college students as well as usage of motorcycles. In noon, traffic flow is very high due to heavy vehicles. In evening, it is moderate and in night time, it is low. Usually the utilization of motor cycles is high. If we considered travel speed, it should be limited in high traffic area. Travel time of a trip is increased tremendously due to long waiting time in the traffic. We cannot reach the destination on time. Also even for the same trip length, if traffic is high, it may severely affect the emergency vehicle running in the road.

Accuracy & Error rate for vehicle count are shown in Table 7. Vehicle classification accuracy & error rate for individual vehicle of BUS, CAR and TRUCK is represented by Table 8. On the other hand, performance metrics of SUMO produces average of 96.63 % accuracy for vehicle count with the average error rate of 3.35 % and STA produces 95.62 % accuracy for vehicle count with the average error rate of 4.37 %. Similarly, for vehicle classification SUMO shows average accuracy of 98 % for bus, 100 % for truck and 93.65 % for car with the error rate of 2 %, 0 % and 6.34 respectively.

STA shows average accuracy of 86.47 % for bus, 76.66 % for truck and 85.92 % for car with the error rate of 13.52 %, 23.32 % and 14.07 % respectively. Configuring Picomixer STA settings for vehicle size is difficult to get correct vehicle count. Careful consideration is needed to set the individual vehicle size which is the influenced parameter for vehicle classification in STA. Fig. 11, Fig. 12 and Fig. 13 describes the comparison view of vehicle count & classification accuracy and error rate at the study area analysis through STA & SUMO. Simulation results using SUMO imitate the real time road network scenario. Similarly, experimental results using STA shows real nature of traffic but it has the limitations in extracting more features from live traffic. It provides the real time values for vehicle count, average speed and traffic volume only. Due to bus, truck and car are the common vehicles available in SUMO and STA. Therefore, these three vehicles are considered for error rate & accuracy calculation of vehicle classification.

5.1. State of Art Comparison with proposed Idea

Table 9 denotes the comparative study with related same studies based on the results obtained by proposed methodology in terms of vehicle types studied, number of parameters used, traffic model either homogeneous/ heterogeneous, and performance metrics for vehicle detection & classification. It implies that various studies are focused on traffic model generation, traffic congestion prediction, traffic flow prediction, real traffic monitoring, vehicle detection & classification, road safety. Also it adopted various methodologies and advanced tools to achieve their research objectives. While comparing with others, our proposed methodology also shows outperformed results in microscopic traffic model generation, vehicle detection and classification.

6. Conclusion

This paper studied the characteristics of road transport network parameters under the heterogeneous background through simulating real time road network scenario in microscopic level using SUMO vehicle transportation simulator and the results are compared with

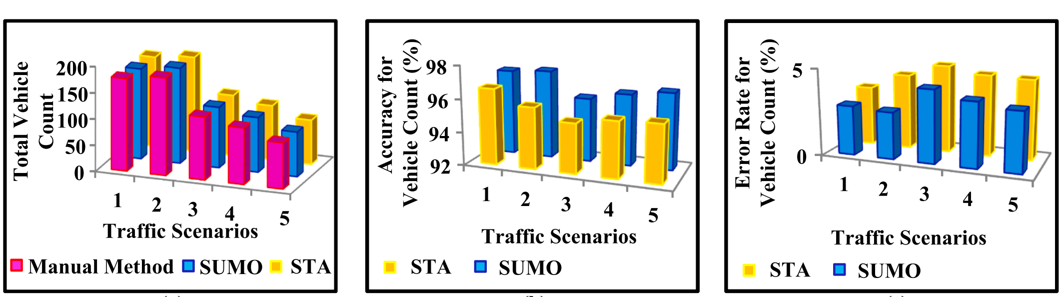


Fig. 11. Comparison of SUMO & STA (a) Vehicle Count, (b) Accuracy for Vehicle Count, (c) Error Rate for Vehicle Count.

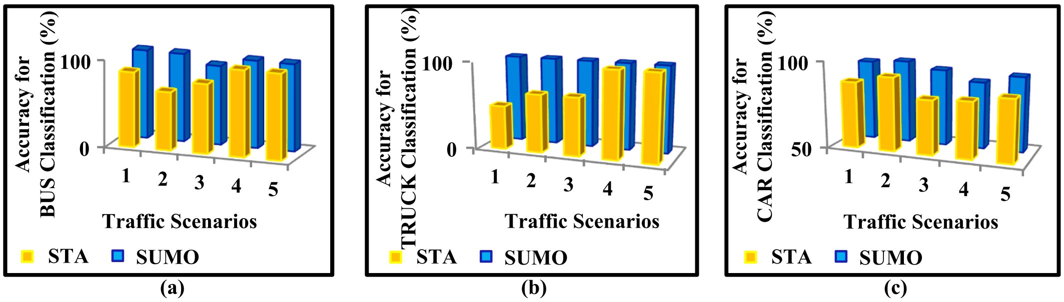


Fig. 12. Comparison of SUMO & STA for Vehicle Classification Accuracy (a) BUS, (b)TRUCK, (c) CAR.

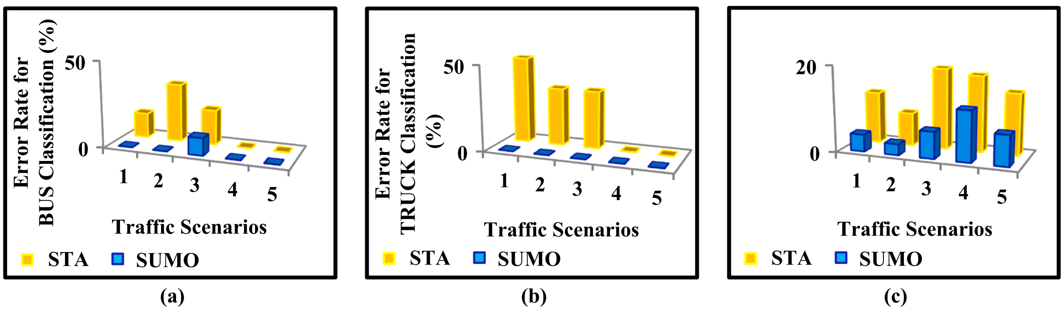


Fig. 13. Comparison of SUMO & STA for Vehicle Classification Error Rate (a) BUS, (b) TRUCK, (c) CAR.

Table 9
Comparison of expert views with our proposed research study.

Reference	Traffic Model Status	Methodology/tools used	Vehicle types studied	Number of road transport parameters considered	Accuracy for Vehicle count (%)	Accuracy for Vehicle classification (%)
[35]	Heterogeneous	Feature Extraction	Cars & bikes	2	97.36	–
[57]	Homogeneous	Haar-like & cascaded Adaboost	Cars	2	–	93.66
[57]	Homogeneous	Haar-like & Adaboost	Cars	2	–	92.28
[57]	Homogeneous	PCA + SVM	Cars	2	–	88.74
[39]	Heterogeneous	SUMO & inductive loop detectors	Passenger cars	2	–	–
[55]	Heterogeneous	SAFEPED model & Leica GPS9000 RTK Survey System	Cars & pedestrian	3	–	–
[50]	Homogeneous	SUMO, Veins 5.0 & OMNET++ 5.4.1	cars	3	–	–
[33]	Heterogeneous	Adaptive background modeling (ABM) & SVM based Kernel Classifier	HMV, LMV, bike & three wheeler	2	88.6	88.8
[33]	Heterogeneous	ABM & Gaussian Radial basis Function	HMV, LMV, bike & three wheeler	2	88.6	85.1
[33]	Heterogeneous	ABM & Polynomial Kernel	HMV, LMV, bike & three wheeler	2	88.6	86.7
Proposed research study	Heterogeneous	SUMO	Car, Bike, Bus, Truck, Pedestrian, Minibus, trailer	8	96.63	97.21
	Heterogeneous	STA		8	95.62	83.01

Picomixer STA which is real time traffic monitoring application along with the performance factors of accuracy and error rate for vehicle count and vehicle classification for five traffic scenarios. Compared to STA, SUMO shows better performance in all aspects. Even though the road transport related parameters & its relationship is familiar in terms of speed, and time to current trend, this paper support the future researchers about the role of STA & SUMO tools for the applications in the transportation filed. Also the outcome of this study will help us to understand about traffic flow prediction & will be used in the applications of rerouting the emergency vehicles, automatic car parking system and automatic tollgate fee collection etc., In future, we planned to extend this work by replacing AI (Artificial Intelligence) based tool for real traffic monitoring to improve the quality of traffic information and further, with the support of machine learning or deep learning algorithm, the same work will be carried out with additional road transport parameters which can have great strength for modeling advanced traffic management system.

7. Limitations and future scope

As like any research paper, this study also has few limitations. In SUMO, produces average values of road network parameters and it is difficult to collect individual vehicle information from the metafile created in SUMO GUI & is manual process. Similarly STA is a simple tool but has the display panel only for the vehicle count & average trip speed. It cannot be used for identifying the low motorized vehicle or bicycle or pedestrian. For future studies, instead of Picomixer STA, this research work can be extended by using another suitable traffic monitoring tool to improve the performance and also to work for developing smart transportation system to design collision management system.

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CRediT authorship contribution statement

Santhiya Ravindran: Data Curation, Methodology, Formal Analysis, Software, Visualization, Writing - original draft, Writing - Review & editing. **Gurukarthik Babu Balachandran:** Conceptualization, Validation, Project administration, Supervision. **Prince Winston David:** Conceptualization, Project administration, Supervision.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.measurement.2024.116233.

Data availability

No data was used for the research described in the article.

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