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POLSKA AKADEMIA NAUK

BULLETIN OF THE POLISH ACADEMY OF SCIENCES
TECHNICAL SCIENCES, Vol. 72(3), 2024, Article number: e149180
DOI: 10.24425/bpasts.2024.149180

CIVIL ENGINEERING

Genetic programming for estimating passenger car equivalent in unsignalized intersections

Aarohi Kumar MUNSHI and **Ashish Kumar PATNAIK** *

Department of Civil & Environmental Engineering, Birla Institute of Technology Mesra, India

Abstract. The study concentrates on two different genetic programming approaches for determining passenger car equivalent (PCE) values and observing the impact on capacity estimation at urban unsignalized intersections. Considering heterogeneous traffic conditions, a new PCE value is introduced to encompass sustainable modes of public transit vehicles, specifically slow-moving three-wheelers (SM3W), commonly known as E-Rickshaws. Since PCE value is considered an important parameter for capacity calculations, the present study considered 14 unsignalized intersections located in Ranchi city of India. An automatic plate recognition system is employed to have the count of vehicular traffic. The methodologies include age-layered population structure genetic programming (ALPSGP), and the offspring selection genetic programming (OSGP) approach that incorporates static and dynamic variables. Based on the significance test and ranking of the genetic programming (GP) models, the OSGP model is recommended as the most appropriate model for heterogeneous traffic. Sensitivity analysis reported that lagging headway (H_i) is the most contributing factor in PCE estimation. The PCE value of SM3W is found to be 0.81 and that could be incorporated as a new classification of vehicles in Indo-HCM. It is observed that evaluated capacity based on PCE values of OSGP performed admirably in both normal and congested traffic situations.

Keywords: passenger car equivalent (PCE); unsignalized intersection; slow-moving three-wheelers (SM3W); urban traffic; sustainable mode; genetic programming.

1. INTRODUCTION

A significant proportion of middle-class and low-income individuals prefer public transportation as their primary mode of commuting [1]. Commuters in the city frequently utilize the environmentally friendly and economically viable E-Rickshaw for short trips within the city. Slow-moving three-wheelers (SM3W) considered E-Rickshaws in city areas have a significant influence on traffic volume and urban traffic congestion along the capacity estimation at intersections. Although traditional cycle rickshaws (with a PCE of 2.0) have been a popular means of public transportation in rural areas and suburbs for decades, newer, more eco-friendly vehicles should be preferred [2]. The SM3W passenger car equivalent (PCE) computation is essential for an efficient transit system. PCE is a persistent challenge owing to various perspectives on computing techniques. However, each of the following techniques attempts to convert a heterogeneous stream into a homogeneous counterpart by considering a vehicle' performance-related factors and ultimately assessing the urban traffic capacity.

The locations, speeds, and rates of acceleration of vehicles on the road are highly variable. In affluent nations, cars represent most of the urban traffic, with trucks and other vehicles constituting a small percentage, whereas, in developing nations, vehicles with a wide range of dynamic and static features and unrestricted maneuverability shares the same road space [3]. In the absence of lane separators, it is more challenging for drivers to maneuver streets with vehicles of varying widths. In addition, assessing and predicting traffic aspects like highway capacity, level of service (LOS), density, etc. within cities and their suburbs becomes complicated. It is quite apparent through comparing homogeneous and mixed traffic that executing traffic operations and designing routes in crowded traffic is a complex task. The PCE yields various kinds of vehicles into a single unit of vehicular flow. In 1965 edition of the Highway Capacity Manual (HCM) introduced PCE to account for the impact of buses and trucks on traffic flow. Considering the standard highway and traffic conditions, PCE was defined as the number of passenger vehicles (standard cars) that a truck or bus displaces from the traffic flow [4].

Preceding studies established that PCE is an essential component in determining traffic capacity. The traffic capacity of a road is the maximum number of vehicles that can be on it at once, given the prevailing traffic, and control circumstances while congestion refers to the increase in the number of vehicles and a substantial decrease in travel production [5]. Several studies adopted numerous methods for accountability of PCE assessment. The vehicle speed and its actual size are crucial considerations in PCE evaluation as suggested by Gautam *et al.*, and a modified density approach is utilized to obtain its values in hilly areas [4]. Chandra *et al*. emphasize the importance of lane width and deliver that the PCE of a vehicle enhances linearly with the width of the carriageway [6]. Mishra *et al*. carried out an area occupancy approach to evaluate the PCE in the context of heterogeneity in Indian traffic and provided consistent results

*e-mail: ashishpatnaik@bitmesra.ac.in

Manuscript submitted 2023-11-10, revised 2024-02-07, initially accepted for publication 2024-02-07, published in May 2024.

to earlier stated values in IRC manuals [7]. Nissari *et al*. studied the delay-based parameters for PCE evaluation at signalized intersections [8]. The PCE computations were also influenced by variables such as headway in the course of roundabouts as unsignalized intersections [9]. For unsignalized intersections, Mohan *et al*. provide several methods to estimate PCE such as capacity at priority movement along with queue clearance rate at the intersection, and the occupancy time method is even considered and presented to be logical with the actual field conditions [10]. Ahmed *et al*. applied an occupancy density linear regression model to develop PCE and motorcycle equivalent factors for two-wheelers [11]. The multiple linear regression approach used in the lane harmonization strategy for PCE in heterogeneous traffic is exclusive to expressways [12]. Biswas *et al*. developed an ANN-based approach for speed prediction in heterogeneous traffic conditions. The speed model developed was utilized to determine PCE for individual vehicle categories. The PCE of each vehicle type also varies with the change in the traffic volume in the traffic stream [13]. Srikanth *et al*. performed a Simulation model VISSIM to depict congestion and to compare estimated PCU values at the level of maximum traffic volume [14]. Granà *et al*. used traffic microsimulation AIMSUM to estimate PCE at turbo-roundabouts and analyzed their values as the composition of heavy vehicles and the overall capacity of a lane varies [15]. Meanwhile, the newly established evolutionary-based genetic algorithm (GA) approach is more popular than earlier stated models. Giuffrè *et al*. used evolutionary-based GA as an optimization tool to calibrate the traffic parameters [16]. Vehicle routing issues are common in transportation logistics. The use of an island genetic algorithm variation with offspring selection adaptive constraint relaxation and adaptive execution of successful operations to address large-scale issue instances with time frames were considered in the study. The obtained outcomes have a considerable positive influence [17]. Furthermore, it is difficult to assess the capacity of an unsignalized intersection considering the complexity of modern urban traffic patterns. Slow-moving passenger vehicles and commercial pickup vans that led to an increase in congestion were not conclusively included in earlier studies. The lack of lane discipline at unsignalized intersections is a concern.

Nevertheless, PCE values based on static vehicle characteristics and lane-disciplined formations are available for several vehicle classes. However, acceleration and deceleration play a crucial role in maneuvering a vehicle in and out of an intersection. It has an impact on the amount of time it takes the vehicle to get through the intersection. The present study attempts to provide the effects of PCE on intersection capacity in urban traffic, therefore a novel PCE model that incorporates the static variable (effective area of a vehicle) and dynamic variables (like vehicle speed at intersection and lagging headway) for accurate estimation of PCE values by employing ALPSGP and OSGP approach. This implies PCE values for different vehicle classes would be helpful for traffic planners and engineers in making key decisions.

In light of the traffic congestion at an unsignalized intersection and an overview of the diverse urban traffic scenarios in developing nations, the following study objectives are outlined.

- To propose an innovative method for assessing PCEs in heterogeneous traffic situations that incorporates both static and dynamic aspects of moving vehicles at unsignalized intersections.
- To assess the impact of PCE on capacity estimation of unsignalized intersections owing to heterogeneous traffic conditions.

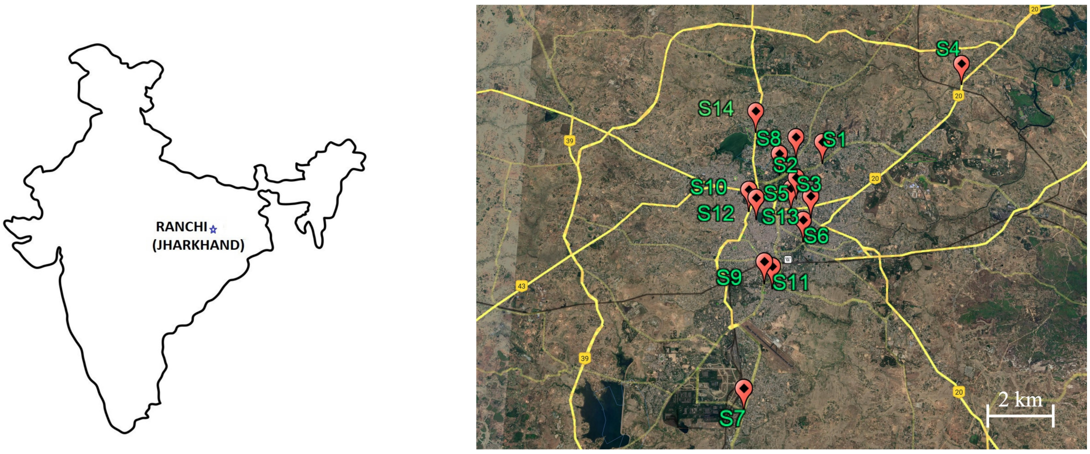
In accordance with these objectives, the paper is organized as follows. The selection of study areas including the data collection technique is enclosed in Section 2. The "Methodology" assigned in Section 3 describes the different techniques such as ALPSGP and OSGP approach for PCE evaluation along with a semi-analytical method. The "Results and discussions" are elaborated on in Section 4. Moreover, the "Conclusions" address the feasibility of the study, with limitations, and future research avenues in Section 5.

2. STUDY AREA AND DATA COLLECTION

The data collection is centered on the prominent unsignalized intersections in the state capital of Jharkhand, India. These are either three-legged or four-legged intersections that combine minor lane traffic with major lane traffic. The following specifications should be satisfied to be considered as one of the designated intersections.

i. It is solely a four-leg intersection/T-intersection mutually perpendicular to each other.
ii. Traffic signalizations are not available at these locations.
iii. All the intersections are situated at grade intersections with no rise and fall.
iv. The intersections are free from any bus stops or other obstructions that might slow down vehicles.

Based on the aforementioned criteria, fourteen major unsignalized intersections in Ranchi City, India were selected. The sites are based purely on their proximity to the commuters' principal routes. The locations of all these places are indicated in Fig. 1. The majority of these sites are in the urban area, while two are on the outskirts. The city locales include RIMS Medical Chowk (S1), Morabadi Chowk (S2), Hari Om Tower (S3), Dangratoli (S5), Bahu Bazaar Chowk (S6), DC Awas Chowk (S8), AG More (S9), Kishoreganj Chowk (S10), Jhanda Chowk (S11), City Lake Road (S12), Plaza Chowk (S13), and Gandhi Nagar Chowk (S14) while BIT Mesra More (S4) and Tupudana Chowk (S7) were selected to serve as locations outside of the city. Owing to the prominence of the routes, the locations were experiencing a significant increase in the volume of traffic. The sites include an institutional area (S4 and S7) located along the side of National Highway 33 (NH 33) and State Highway 3 (SH 3), respectively. A medical institution (S1) on the minor lane along with a major lane comprising multiple hospitals and clinics at or near the intersection. The site (S4) features a sports complex with stadiums near the government residential quarters, whereas the remaining sites have a commercial area adjacent to the residential complex on minor roads. The traffic patterns were recorded with a high-definition video camera, which was placed at a sufficient height, commonly a roadside high-rise, to provide a top-down or angled view of the



(a) Ranchi on map of India (b) Location of data collection sites

Fig. 1. Representation of city and sites of the study

intersection. This study data was collected in the year 2022, after the implementation of post-COVID-19 regulations. The videos were recorded on a weekday in daylight. Traffic volume was calculated using 15-minute intervals of peak flow and records were made for two hours while there was continuous queuing.

Data was obtained from a wide range of locations and at a range of times, including 9 am to 11 am for commercial and institutional places, 12 pm to 2 pm for hospital sites, and 4 pm to 6 pm for residential and sports facility areas. The afternoons appear to be peak hours for hospitals since visitors are permitted to meet their patients even owing to lunch hours. The video was viewed, and data was retrieved using widescreen monitors. The optical recognition system (Automatic Number Plate) covered a count for the number of vehicles crossing the intersection, and the vehicles were manually tallied from the recordings to provide an accurate count of different kinds of vehicles. All the vehicles were categorized into eight different classes based on their physical dimensions and operational capabilities. The classification comprises motorized two-wheelers (2W), slow-moving three-wheelers (SM3W), three-wheelers (3W), standard cars (SC), large cars (LC), mini commercial vans (MCV), heavy vehicles (HV) and bicycles (BCY). The sources for vehicle dimensions used in previous PCE investigations [6] are as per the IRC:003 [19], and since then the traffic patterns and vehicle sizes have significantly changed during the last two decades. To that end, the study utilized manufacturer-supplied dimensions for the most widely used vehicle models in India across all vehicle classes. This lacuna enhances the current relevance and scope of the study. The highly specific vehicular dimensions of various classes of vehicles and traffic volume at each location are provided in Table 1 and Table 2, respectively. The provided data in Table 2 shows that SM3W vehicles are more prevalent in urban traffic than on highways.

Table 1
Physical and effective areas of vehicles

Specifics	Vehicles included	Length (m)	Width (m)	Physical area (square meter)	Effective area (square meter)	^{a}PCE
2W	Motorcycle, gearless scooter	2.03	0.79	1.6	3.13	0.25
SM3W	E – Rickshaw	2.8	1	2.8	4.48	–
3W	Auto, CNG-fueled auto	2.93	1.48	4.34	7.27	1.0
SC	Hatchback cars	3.65	1.62	5.91	9.56	1.0
LC	Sedan, SUVs	4.79	1.85	8.86	13.65	–
MCV	Pickups, towing vehicles	3.79	1.5	5.69	9.48	1.8
HV	Bus, truck, ambulance	7.19	2.34	16.82	24.01	4.0
BCY	Bicycle	1.9	0.45	0.86	1.62	0.39

Note: 2W – Two-wheelers, SM3W – Slow-moving three-wheelers, 3W – Three-wheelers, SC – Standard cars, LC – Large cars, MCV – Mini commercial vans, HV – Heavy vehicles, BCY – Bicycles, ^{a}PCE – Passenger car unit as per IRC [18]

Table 2
Classified vehicular volume counts (vehicles/hr)

Sites	Camera position	2W	SC	LC	3W	SM3V	HV	BCY	MCV	Actual vehicle	Detected vehicle	Accuracy percentage
S1	Top	2587	772	530	764	173	24	60	31	4941	4382	89.78
S2	Top	2421	480	376	304	491	2	312	38	4424	3834	93.24
S3	Top	2259	489	334	315	476	18	299	39	4229	3568	90.79
S4	Top	2016	517	375	483	77	143	168	73	3852	3389	91.99
S5	Top	2471	474	323	384	317	17	337	64	4387	3728	92.05
S6	Top	2944	447	259	562	379	33	267	32	4923	4257	91.43
S7	Side	2182	410	382	346	58	124	153	81	3736	3016	84.18
S8	Top	1627	358	264	218	137	3	87	15	2709	2421	92.33
S9	Top	3983	968	646	627	464	47	612	74	7421	6519	95.74
S10	Top	2919	707	472	636	231	9	504	109	5587	4839	95.20
S11	Side	1642	329	87	348	243	8	318	134	3109	2263	81.08
S12	Side	1748	215	141	241	146	2	159	26	2678	2087	82.85
S13	Top	3371	572	361	463	307	7	284	58	5423	4689	91.24
S14	Top	1537	481	293	389	156	4	127	47	3034	2754	94.74

Note: 2W – Two-wheelers, SM3W – Slow-moving three-wheelers, 3W – Three-wheelers, SC – Standard cars, LC – Large cars, MCV – Mini commercial vans, HV – Heavy vehicles, BCY – Bicycles

3. METHODOLOGY

The methodology section comprises three parts. The first part gives a proposed PCE model based on a semi-analytical approach for an unsignalized intersection. Subsequently, the rest of the two models are developed by employing ALPSGP and OSGP for PCE estimation.

3.1. Semi-analytical PCE model

In the present study, the effective area is referred to as the space occupied by the vehicle under normal traffic conditions, encompassing both the clearing area and the actual dimensions of the vehicle. It is primarily governed by the vehicle size as well as its maneuverability characteristics like the speed of the vehicle at intersections. The lane geometry and traffic conditions at the intersection also influence the effective area parameters. Figure 2 depicts an apparent representation of a subject vehicle effective area. Consequently, the effective area is provided by equation (1), and the fundamental formula for PCE, by taking into consideration all contributing variables, is stated in equation (2) [20]

$$A_i = L_i\,(W_i + C_i)\,, \tag{1}$$

where A_i is the effective area, L_i is the length, W_i is the width, and C_i is the total lateral clearance (C_{ir} and C_{il} are right and left clearances of the vehicle, respectively) of the subject vehicle i.

$$\mathrm{PCE}_i = \frac{A_i V_c}{A_c V_i} \cdot \frac{H_i}{H_c}\,, \tag{2}$$

where PCE_i is passenger car equivalent of subject vehicle i, V_c, A_c, H_c are the vehicular speed at an intersection in km/h, the effective area in square meters and mean lagging headway in seconds of the standard car. V_i, A_i, H_i are the vehicular speed at an intersection in km/h, effective area in square meters, and mean lagging headway in seconds of subject vehicle i.

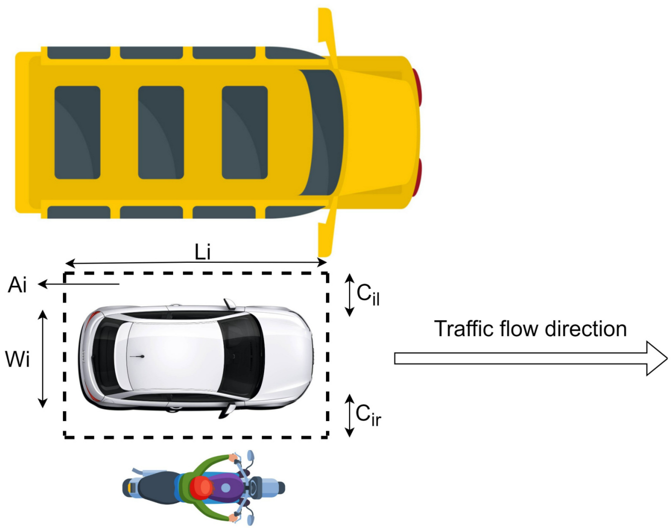
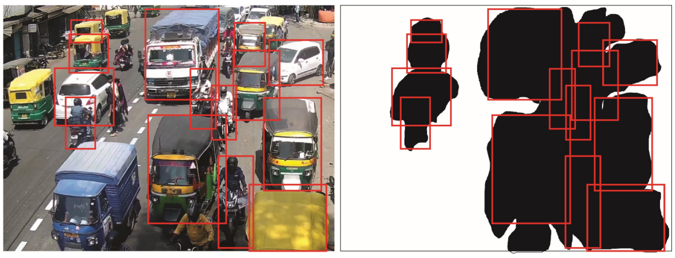


Fig. 2. Representation of effective area

The space around a vehicle that caters to its movement without colliding with other vehicles is identified as lateral clearance. Thus, clearance in heterogeneous traffic is contingent on several variables, including the type of vehicle, its pace, the driver's characteristics, the proximity to other vehicles, and the state of the traffic. At unsignalized intersections, clearance distances are tracked for each kind of vehicle, and subsequently, the average lateral clearances are selected. The recordings were converted to images, to be subsequently segmented and morphed to distinguish between jammed and unoccupied street space using CorelDRAW. In Fig. 3b, there is space available in lanes in normal traffic conditions for lateral clearance inclusion in getting an effective area; however, in Fig. 4b, the overlapped physical areas of vehicles are observed. Since the mobility of a vehicle depends on its size, it is evident from the video recordings that larger vehicles require adequate lateral clearance. The clearance distance in normal traffic conditions (Fig. 3a) adopted for larger vehicles such as SC, LC, HV, MCV, and 3W are 1 m [21], whereas the values for BCY, SM3W, and 2W are 0.4 m, 0.6 m, and 0.75 m, respectively [20]. Observations consistently show that SM3Ws have lower lateral clearance than 2Ws. In a crowded (jammed) condition, as shown in Fig. 4a, clearance values are minimal and can even be decreased to zero ($C_i = 0$). Thus, while calculating the PCE in heavy traffic situations, the effective area is precisely the same as the physical area of the vehicle.

(a) Vehicle identification (b) Vehicle effective area with lateral clearance

Fig. 3. Effective area selection on normal traffic flow at site S9



(a) Vehicle identification (b) Vehicle physical area with zero clearance

Fig. 4. Effective area selection on congested traffic flow at site S1

Further, the lagging headway spans a combination of the length of the vehicle and the distance between the vehicles. It is determined by monitoring the duration between the rear bumpers of the leading and following vehicles. Headway is used to calculate both the lane capacity and the longitudinal gaps between vehicles [21]. The wide range of vehicles present at any given time renders it challenging to precisely measure the lateral clearance and lagging headways of running vehicles. So, the durations and distances were calculated using the video recordings frame by frame and the corresponding lagging headway of different vehicles considered in the study had a range of 2.3 seconds to 4.7 seconds. Further, the radar gun was used to assess the subject vehicle speed at intersections under normal and congested flow conditions as well. The measurement of the speeds of target vehicles was carried out by employing a radar gun which follows the principle of Doppler effect [22]. Considering that the speed of vehicles varies widely, average values are selected to limit the variance and to produce significant results. The average speeds of varied categories of vehicles at intersections are between 11 km/h to 26 km/h.

3.2. GP approach

Genetic programming (GP) is a technique that strives to accomplish issues by recognizing and merging programmable components that can produce desirable outcomes [23]. Program components, such as designed features, are utilized for classification and regression concerns. GP classification and regression solutions include fundamental components that define the variance causing the simulated response. Symbolic regression concerns utilizing a random data distribution and fitting the data with the highest acceptable symbolic formula. RMSE (root mean square error) or MSE (mean squared error) are commonly used to assess an individual's fitness. The PCE model performance under heterogeneous vehicular traffic flow was assessed using two different evolutionary-based GP approaches (ALPSGP and OSGP). The dependent variable in these two models is (PCE_i), while the explanatory variables are effective area (A_i), vehicle speed at intersection (V_i) and lagging headway (H_i).

In contrast to standard evolutionary algorithms (EA), age-layered population structure (ALPS) separates its population into layers based on age and periodically introduces newly created individuals into the youngest layer. Through age-based competition limits, younger persons can flourish without being undermined by their elders. In practice, ALPS lets multiple EAs run at the same time, which inhibits solutions from heading together too rapidly [24]. In the offspring selection genetic programming regression model (OSGP), the selection of offspring is the execution stage in the regression model progression, which also includes selecting parents, performing a crossover, and introducing mutations. The individuals from the population are considered for further breeding based on their fitness ratings during the offspring selection stage. An improved solution is indicated by a higher fitness score [25].

4. RESULTS AND DISCUSSION

The section is comprised of five parts. The first part describes the development of the ALPSGP and OSGP models. The significance test of the two models and the selection of the best model based on MRI is given in the subsequent section. The following part includes a sensitivity analysis of the preferred GP model. In addition, the next part discusses the comparison of PCE values from the existing semi-analytical method and the selected GP model with the recommended Indo-HCM PCE values at the unsignalized intersection. The effect of PCE on capacity evaluation is addressed further in the section, and practical applications are outlined at the end.

4.1. Development of ALPSGP and OSGP models

A preliminary evaluation was performed before creating the models to determine the reliance of various variables regarding the dependent variable. The level of linear dependence between two variables was analyzed utilizing the Pearson correlation; outcomes are presented in Table 3.

Table 3
Pearson correlation among variables

	PCE_i	A_i	H_i	V_i
PCE_i	1.0000			
A_i	0.8872	1.0000		
H_i	0.8961	0.8701	1.0000	
V_i	–0.9041	–0.7934	–0.7863	1.0000

Note: PCE_i – Passenger car equivalent of subject vehicle i
A_i – Effective area of subject vehicle i in square meter
H_i – Mean lagging headway of subject vehicle i in seconds
V_i – Vehicular speed of subject vehicle i at an intersection in km/h

The linear dependence of explanatory variables such as V_i is around –0.9041 while that of A_i and H_i is approximately 0.8872 and 0.8961, respectively. As the values lie between Pearson's 'r' value –1 to 1, it indicates that dependent and explanatory variables are highly correlated among them [26]. Thus, the explanatory variables A_i, V_i and H_i are used to model the PCE_i value. A total of 196 sample points (observations from both minor and major roads of an unsignalized intersection) were used in the analysis. 158 samples (covering 70% of the sample) were utilized for training the model, while the remaining samples were used for testing. Each sample point represented a node in a hierarchical software application, and each sample point originated from the same population. The genotype is interpreted in ALPSGP and OSGP regression as a symbolic value. Numerical constants and symbolic variables are merely arranged in a binary tree to form the symbolic statement. The following equations (3) and (4) provide the model equation for the ALPSGP and OSGP models, respectively, while Fig. 5 depicts the tree-based mathematical expression of the OSGP model.

$$PCE_i = C_0 H_i + C_1 A_i + (C_2 H_i)^{-1} + C_3 , \tag{3}$$

$R^2 = 0.922$, RMSE = 0.308, where $C_0 = -0.12355$, $C_1 = 0.037856$, $C_2 = -0.19754$, $C_3 = 5.374$.

Each node of a tree represents a function or operation, while its leaves represent constants or variables. Several iterations of ALPSGP and OSGP regression were performed to achieve the optimal solution (the PCE_i). The trees yield improved solutions over time as a result of gene crossover and mutation.

$$PCE_i = C_0 H_i + C_1 V_i + H_i A_i e^{C_2 H_i} C_3 + C_4 , \tag{4}$$

$R^2 = 0.945$, RMSE = 0.261, where $C_0 = 0.72268$, $C_1 = -0.10729$, $C_2 = -0.45511$, $C_3 = 0.039803$, $C_4 = 1.135$.

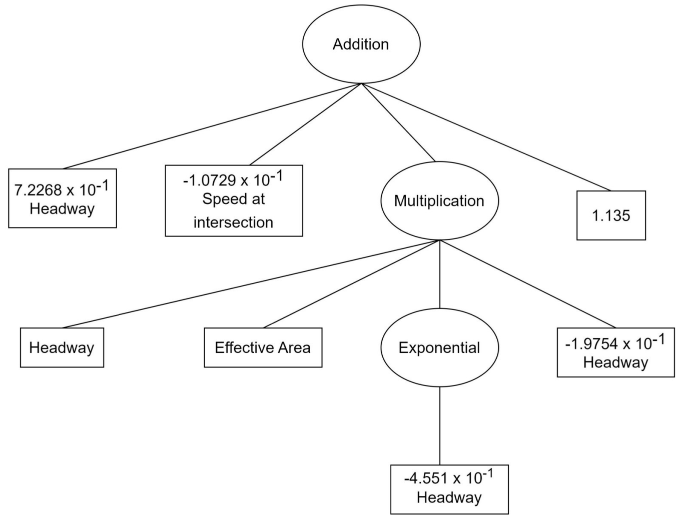


Fig. 5. Tree-based structure of OSGP regression model

4.2. Significance test and rank

Multiple statistical variables were employed to conduct an overall prediction evaluation of the two built PCE models, ALPSGP and OSGP. The models were then validated using the MRI from equation (5) [27]. Models are ranked using different metrics such as, R1 is based on best-fit calculations (includes R^2 and the Nash-Sutcliffe efficiency coefficient E), while R2 is based on error variables like the root-mean-squared error (RMSE), average absolute error (AAE) and maximum absolute error (MAE), R3 represents the ranking of a model based on arithmetic calculations (mean μ and standard deviation σ) of the ratio of natural logarithm of predicted and observed PCE values (PCE_P/PCE_O), R4 ranking is based on 50% and 90% cumulative probability (CP_{50} and CP_{90}) values produced from a cumulative probability plot of PCE_P/PCE_O (ratio of predicted and observed PCE values), and R5 relies on the prediction of PCE value within ±20% accuracy level, computed using the histogram and lognormal distribution of PCE_P/PCE_O.

$$\mathrm{MRI} = R1 + R2 + R3 + R4 + R5. \tag{5}$$

Literature findings indicate as the predicted PCE (PCE_P) equals the measured PCE (PCE_O), the mean and standard deviation of PCE_P/PCE_O are 1 and 0, respectively. Predictive models with values closer to 1 or 0 are deemed to be more accurate. Under and overpredictions are indicated by a CP_{50} ratio below and above 1, respectively. CP_{90} represents the variance in PCE_P/PCE_O values for all observations. The effectiveness of a predictive model improves when CP_{50} and CP_{90} values lie closer to 1. The MRI values for each PCE model presented in the study are outlined in Table 4, and the result indicated that the OSGP model outperformed the ALPSGP model with MRI = 5 as well as an overall ranking of 1.

4.3. Sensitivity analysis

Considering the results of equation (5), it is evident that the OSGP model is best suited to modeling heterogeneous traffic

Table 4
Rank of developed GP models

Model	Data	Best fit calculations			Error measuring parameters				Arithmetic calculation of PCE_P/PCE_O			Cumulative probability of PCE_P/PCE_O			±20% Accuracy (%)			Overall rank	
		R^2	E	R1	RMSE	AAE	MAE	R2	μ	σ	R3	Ratio at CP_{50}	CP_{90}	R4	Histo-gram	Log-normal	R5	MRI	Normal rank
ALPSGP	Training	0.922	0.922	1	0.308	0.236	1.297	2	1.004	0.264	2	1.025	1.334	2	81.72	78.73	2	7	2
	Testing	0.919	0.917		0.297	0.233	1.066		1.011	3.11		0.973	1.428		81.28	77.12			
OSGP	Training	0.945	0.945	2	0.261	0.196	1.12	1	0.998	0.253	1	0.998	1.295	1	83.68	82.12	1	5	1
	Testing	0.876	0.866		0.364	0.262	1.227		0.926	0.28		0.905	1.195		82.21	79.29			

Note: R^2 – Coefficient of determination, E – Nash–Sutcliffe coefficient, AAE – Average Absolute Error, MAE – Maximum Absolute Error, RMSE – Root Mean Square Error

flows. A sensitivity analysis was conducted to evaluate the relative significance of the explanatory variable (the input variable contribution to the development of the model) [28]. The ranking of each explanatory variable is listed in Table 5. Most of the variance in PCE values at unsignalized intersections can be attributed to variations in lagging headway (H_i) sensitivity, which was observed to have the significant effects (45.65%). In urban streets, it is usual for HV and MCV to maintain a safe distance between themselves and the vehicles in front of them when maneuvering, contributing to the longer time required to traverse unsignalized intersections and resulting in significantly higher PCE values when compared to 2W, 3W, and SM3W.

Table 5
Sensitivity analysis of the explanatory variables of the OSGP model

Variables	Sensitivity %	Rank
A_i	14.18202	3
V_i	40.16647	2
H_i	45.65151	1

Note: A_i – Effective area of subject vehicle i in square meter
H_i – Mean lagging headway of subject vehicle i in seconds
V_i – Vehicular speed of subject vehicle i at an intersection in km/h

4.4. Comparison among existing PCE models

PCE values were calculated for each of the sites under both the normal and the heavy traffic flow conditions in which the corresponding values are averaged to obtain theoretical PCE values. The research findings are based on the existing vehicle size as well as the inclusion of motorized passenger vehicles as slow-moving three-wheelers (SM3W). In normal traffic, PCE values for smaller-sized vehicles such as the 2W and 3W were usually higher than in congested conditions. The PCE values for SM3W are nearly identical in both traffic conditions. Findings indicate that, in normal conditions, small-sized vehicles have sufficient space for maneuvering and maintain significant speeds at an intersection to prevent collisions. In dense urban traffic, smaller-sized vehicles such as 2W, and SM3W have practically minimal clearance, drastically limiting their effective area. They can usually drive more quickly than SC, LC, MCV, and HV allowing them to rapidly maneuver through congested areas and causing traffic jams for larger vehicles. Consequently, it influences their PCE, lowering its values, and lane capacity in congested locations is increased.

The comparison between the semi-analytical PCE values, evaluated PCE values relying on the OSGP approach, and the Indo-HCM values is indicated in Table 6. Based on the comparison, it is observed that the PCE value for SM3W is not mentioned in the Indo-HCM recommendation. The sustainable and cost-effective mode of transit within the city for local movement has a significant effect on traffic volume; thus, SM3W PCE value must be considered. Moreover, for heterogeneous urban traffic scenarios at unsignalized intersections, the evaluated PCE values are neither underestimated nor overestimated.

Table 6
PCE values of existing models

Vehicular classification	Semi-analytical PCE	Evaluated PCE	Indo-HCM PCE
SC	1.00	1.00	1.00
2W	0.23	0.32	0.34
SM3V	0.46	0.81	–
3W	0.92	0.98	0.98
MCV	1.04	1.22	1.7
LC	1.86	1.53	1.29
HV	9.10	3.87	2.29

Note: SC – Standard cars, 2W – Two-wheelers, SM3W – Slow-moving three-wheelers, 3W – Three-wheelers, MCV – Mini commercial vans, LC – Large cars, HV – Heavy vehicles

4.5. Effect of PCE on capacity

The capacity of minor roads at unsignalized intersections is estimated as given in equation (6) in the Indo-HCM approach [29]

$$C_x = a \, . V_{cx} \frac{e^{-Vcx(t_{cx}-b)/3600}}{1-e^{-Vcx(t_{fx}/3600}}, \tag{6}$$

where C_x is the capacity of a movement 'x' (in PCE/hr), V_{cx} is the conflicting flow rate corresponding to a specific movement (in PCE/hr), t_{fx} and t_{cx} are the follow-up time and critical gap of standard passenger cars and for a movement 'x' in seconds, respectively. a and b are adjustment factors based on an intersection's geometrics.

The HCM 2000 and HCM 2010 equations were formulated in the Indo-HCM 2017 guidelines based on Indian road standards and traffic conditions. Furthermore, the adjustment factors for three and four-legged unsignalized intersections are different, as specified in the manual. Analysis of traffic patterns by videography indicates that the capacity of major roads in unsignalized intersections is around 2.6 times that of minor streets. According to video recordings, the major and minor roads are two lanes wide and undivided. Subsequently, an intersection capacity is estimated by combining the major and minor lane traffic capacities.

Figure 6 compares the observed capacities on-site to the predicted capacities providing Pearson's 'r' and R-square value of linear fit line. Estimates of three different predicted capacities are obtained using three different PCE values: the semi-analytical PCE approach in the existing method, the evaluated PCE as per the OSGP model, and the PCE values recommended by Indo HCM. The variation in capacity is because the semi-analytical PCE values for the HV and 2W are excessively high and low, respectively. In urban streets, the heterogenous traffic conditions rely primarily on SM3W, 2W, and 3W. Regardless of Indo HCM capacity, which lacks the PCE value for SM3W while estimating (as identical PCE is assumed for SM3W and 3W), the predicted capacity based on evaluated PCE as per OSGP model is within the confidence interval.

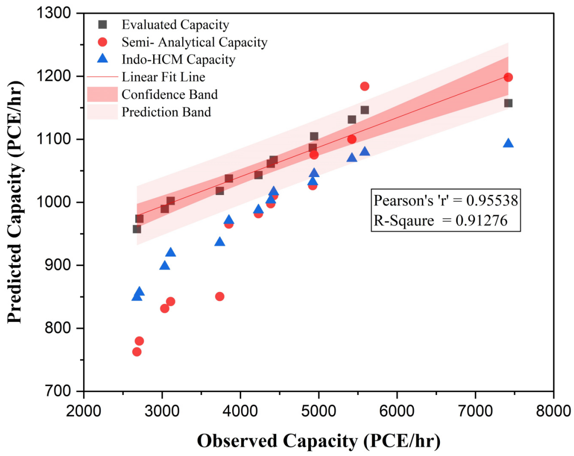


Fig. 6. Comparative analysis of observed and predicted capacities

The confidence and prediction intervals and the linear fit line are fundamental elements in statistical analysis that present significant insights regarding the model confidence and reliability. The linear fit line represents the best-fitting straight line through a set of data points. It is utilized for making predictions and comprehending the overall pattern in the data. A confidence band is a statistical interval representing the likely range in which the actual trend line is expected to lie, with a specified level of confidence. The uncertainty associated with parameter estimates increases as the width of the band increases. The prediction band signifies that the future individual data points are expected to fall within the band. Its width surpasses the confidence band due to its consideration of both individual observation variability and uncertainty in predicting the mean response. After extensive capacity predictions, the evaluated capacity of the OSGP PCE model performed impressively in both normal and congested traffic situations.

4.6. Practical application

The outcomes of the proposed study are applicable for practical uses. The evaluated PCE values are easy to implement, understand, and widely acceptable due to their simplified approach. These values appear to be feasible for urban unsignalized intersections under heterogeneous traffic conditions. The evaluated PCE values for different vehicles can assist traffic planners and engineers in estimating traffic volume and anticipating lane capacity in forthcoming smart city projects and tier II cities in India. Insight of eco-friendly environment, the evaluated PCE value for SM3W as per the OSGP model could be incorporated for a reliable estimate of urban traffic capacity.

5. CONCLUSIONS

The PCE of a vehicle is a comprehensive value that is determined by a diverse range of variables that influence the way a vehicle behaves in a traffic flow. These variables include driving speed at intersections, lagging headway, lateral clearance, and physical dimensions of the vehicle. The HCM approach regarding PCE values is based on ideal conditions. Nevertheless, the subject vehicle and neighboring cars in traffic flows may not necessarily be of the same vehicle class. It is not always possible to achieve the ideal scenario on a site. The composition of urban traffic was found to be heterogeneous. The mean traffic share of motorized vehicles at various sites varied as follows: 56% (2W), 6% (SM3W), 10.1% (3W), 11.9% (SC), 7.9% (LC), 1.4% (MCV) and 0.8% (HV) of total vehicular counts. PCE has a substantial impact on urban traffic congestion and estimating traffic capacity. Vehicle PCE values can also alter dramatically with changes in geometrics of intersection and traffic scenarios. Evaluated PCE values as per the OSGP model were proposed to manage traffic demand in metropolitan cities as well, where commuters even prefer slow-moving three-wheelers (SM3W) for local transit in suburbs. The following conclusions are drawn from the study.

- In compliance with existing car dimensions, the evaluated PCE values show that each heavy vehicle (HV), commercial pick-up van (MCV), and large cars (LC) can accommodate 3.87, 1.22, and 1.53 of standard cars in a congested urban traffic lane, respectively.
- The lower PCE values of 0.81 and 0.32 are observed for E-rickshaws (SM3W) and two-wheelers (2W), respectively, which increase lane capacity in urban areas. Three-wheelers fueled by compressed natural gas (CNG) have PCE values that are approximately comparable to those of standard cars.
- ALPSGP uses an age-based population structure to improve convergence. As a result, it is well suited to challenges that require immediate attention. However, it may not be as effective at determining optimal solutions as other models. OSGP, a subclass of GP, is a dynamic mutation and crossover operator-based approach to problem-solving. It was validated to be more effective than conventional GP, albeit it may take a while to establish a solution than ALPSGP.

Since most heavy vehicles were prohibited from entering the city during the day, buses and military trucks made up the vast majority of the HV. It is indeed difficult to compute the speed of a vehicle. The speed of SM3W and HV appears to be low for a radar gun to be accurately determined in certain situations. Nevertheless, the inflow of electric two-wheelers and electric autos makes it feasible to improve the traffic capacity of urban streets as their dimensions are to be reduced, and this makes the transportation stream more conscious of the necessity for future research in PCE assessment and encourages the use of eco-friendly mode of vehicles for public transit.

REFERENCES

[1] R.G. Mercado, A. Paez, S. Farber, M.J. Roorda, and C. Morency, "Explaining transport mode use of low-income persons for journey to work in urban areas: a case study of Ontario and Quebec," *Transportmetrica*, vol. 8, no. 3, pp. 157–179, May 2012, doi: 10.1080/18128602.2010.539413.

[2] "IRC 064: Guidelines for Capacity of Roads in Rural Areas (First Revision)".

[3] S.K. Singh, "Review of Urban Transportation in India," *J. Public Transp.*, vol. 8, no. 1, pp. 79–97, Jan. 2005, doi: 10.5038/2375-0901.8.1.5.

[4] A. Gautam, A. Das, K.R. Rao, and G. Tiwari, "Estimation of PCE values for hill roads in heterogeneous traffic conditions," *Transp. Lett.*, vol. 10, no. 2, pp. 83–91, Mar. 2018, doi: 10.1080/19427867.2016.1190884.

[5] A. Loder, L. Ambühl, M. Menendez, and K.W. Axhausen, "Understanding traffic capacity of urban networks," *Sci. Rep.*, vol. 9, no. 1, p. 1, Nov. 2019, doi: 10.1038/s41598-019-51539-5.

[6] S. Chandra and U. Kumar, "Effect of Lane Width on Capacity under Mixed Traffic Conditions in India," *J. Transp. Eng.*, vol. 129, no. 2, pp. 155–160, Mar. 2003, doi: 10.1061/(ASCE)0733-947X(2003)129:2(155).

[7] R. Mishra, P. Kumar, S.S. Arkatkar, A.K. Sarkar, and G.J. Joshi, "Novel Area Occupancy–Based Method for Passenger Car Unit Estimation on Multilane Urban Roads Under Heterogeneous Traffic Scenario," *Transp. Res. Rec.*, vol. 2615, no. 1, pp. 82–94, Jan. 2017, doi: 10.3141/2615-10.

[8] H. Nassiri, S. Tabatabaie, and S. Sahebi, "Delay-based Passenger Car Equivalent at Signalized Intersections in Iran," *Promet*, vol. 29, no. 2, p. 2, Apr. 2017, doi: 10.7307/ptt.v29i2.2040.

[9] C. Lee, "Developing Passenger-Car Equivalents for Heavy Vehicles in Entry Flow at Roundabouts," *J. Transp. Eng.*, vol. 141, no. 8, p. 04015013, Aug. 2015, doi: 10.1061/(ASCE)TE.1943-5436.0000775.

[10] M. Mohan and S. Chandra, "Three methods of PCU estimation at unsignalized intersections," *Transp. Lett.*, vol. 10, no. 2, pp. 68–74, Mar. 2018, doi: 10.1080/19427867.2016.1190883.

[11] A. Ahmed *et al.*, "Estimating Passenger Car Equivalent Factors for Heterogeneous Traffic Using Occupancy-Density Linear Regression Model," *Transp. Res. Rec.*, vol. 2676, no. 8, pp. 209–220, Aug. 2022, doi: 10.1177/03611981221083289.

[12] J.S. Yeung, Y.D. Wong, and J.R. Secadiningrat, "Lane-harmonised passenger car equivalents for heterogeneous expressway traffic," *Transp. Res. Part A-Policy Pract.*, vol. 78, pp. 361–370, Aug. 2015, doi: 10.1016/j.tra.2015.06.001.

[13] S. Biswas, S. Chandra, and I. Ghosh, "Estimation of Vehicular Speed and Passenger Car Equivalent Under Mixed Traffic Condition Using Artificial Neural Network," *Arab. J. Sci. Eng.*, vol. 42, no. 9, pp. 4099–4110, Sep. 2017, doi: 10.1007/s13369-017-2597-9.

[14] A.M. Seelam Srikanth, "A modified approach for estimation of Passenger Car Units on intercity divided multilane highways," *Arch. Transp.*, vol. 42; no 2, pp. 65–74, 2017, doi: 10.5604/01.3001.0010.0528.

[15] A. Granŕ, T. Giuffrč, E. Macioszek, and F. Acuto, "Estimation of Passenger Car Equivalents for Two-Lane and Turbo Roundabouts Using AIMSUN," *Front. Built Environ.*, vol. 6, p. 86, 2020, doi: 10.3389/fbuil.2020.00086.

[16] O. Giuffrč, A. Granŕ, M.L. Tumminello, and A. Sferlazza, "Capacity-based calculation of passenger car equivalents using traffic simulation at double-lane roundabouts," *Simul. Model. Pract. Theory*, vol. 81, pp. 11–30, Feb. 2018, doi: 10.1016/j.simpat.2017.11.005.

[17] S. Vonolfen, M. Affenzeller, A. Beham, and S. Wagner, "Solving large-scale vehicle routing problem instances using an island-model offspring selection genetic algorithm," in *3rd IEEE International Symposium on Logistics and Industrial Informatics*, Hungary, Aug. 2011, pp. 27–31, doi: 10.1109/LINDI.2011.6031155.

[18] "Draft Guidelines for Capacity of Urban Roads in Plain Terrain IRC: 106 (First Revision)," *The Indian Roads Congress*, 2022.

[19] "IRC 003: Dimensions and Weights of Road Design Vehicles," *The Indian Roads Congress*, 1983.

[20] A.K. Munshi and A.K. Patnaik, "Development of PCU Model for Unsignalised Intersection: A Case Study of Ranchi City," in *Recent Trends in Transportation Infrastructure, Volume 2*, A. Agarwal, S. Velmurugan, and A.K. Maurya, Eds., in *Lecture Notes in Civil Engineering*. Singapore: Springer Nature, 2023, pp. 207–218, doi: .

[21] A.K. Patnaik, Y. Krishna, S. Rao, and P.K. Bhuyan, "Development of Roundabout Entry Capacity Model Using INAGA Method for Heterogeneous Traffic Flow Conditions," *Arab. J. Sci. Eng.*, vol. 42, no. 9, pp. 4181–4199, Sep. 2017, doi: 10.1007/s13369-017-2677-x.

[22] S.-L. Jeng, W.-H. Chieng, and H.-P. Lu, "Estimating Speed Using a Side-Looking Single-Radar Vehicle Detector," *IEEE Trans. Intell. Transp. Syst.*, vol. 15, no. 2, pp. 607–614, Apr. 2014, doi: 10.1109/TITS.2013.2283528.

[23] R. Sahani, A. Ojha, and P.K. Bhuyan, "Service levels of sidewalks for pedestrians under mixed traffic environment using Genetic Programming clustering," *KSCE J. Civ. Eng.*, vol. 21, no. 7, pp. 2879–2887, Nov. 2017, doi: 10.1007/s12205-017-0042-y.

[24] A. Awuley and B.J. Ross, "Feature selection and classification using age layered population structure genetic programming," in *2016 IEEE Congress on Evolutionary Computation (CEC)*, Canada, Jul. 2016, pp. 2417–2426. doi: 10.1109/CEC.2016.7744088.

[25] B. Burlacu, K. Yang, and M. Affenzeller, "Population diversity and inheritance in genetic programming for symbolic regression," *Nat Comput*, Jan. 2023, doi: 10.1007/s11047-022-09934-x.

[26] R. Taylor, "Interpretation of the Correlation Coefficient: A Basic Review," *J. Diagn. Med. Sonog.*, vol. 6, no. 1, pp. 35–39, Jan. 1990, doi: 10.1177/875647939000600106.

[27] S.K. Beura and P.K. Bhuyan, "Modeling Quality of Bicycle Accommodations on Urban Road Segments Using Functional Networks and Multivariate Adaptive Regression Spline Techniques," *Transportation Research Board 96th Annual Meeting*, 2017. [Online]. Available: https://trid.trb.org/view/1437546 (Accessed: Jan. 05, 2023).

[28] E. Cuenca, "Highway Capacity Manual Transportation," Research Board-National Research Council. [Online]. Available: https://www.academia.edu/26524134/Highway_Capacity_Manual_Transportation_Research_Board_National_Research_Council (Accessed: Feb. 09, 2023).

[29] P. Ryus, M. Vandehey, L. Elefteriadou, R.G. Dowling, and B.K. Ostrom, "New TRB Publication: Highway Capacity Manual 2010," *TR News*, vol. 273 (March-April 2011), pp. 45–48, Mar. 2011.