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Modelling Service Quality Offered by Signalized Intersections from Automobile Users' Perspective

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Abstract

This article proposes modelling service quality offered by signalised intersections, nodal focuses in a transportation network, in urban Indian context. Indian traffic is generally heterogeneous in nature which implies non-motorised vehicles and pedestrians, sharing same space with motorised vehicles. All possible geometric, traffic and built-environmental data were collected from 45 diversified signalised intersections located in one of the metropolitan Indian cities Kolkata. Along with these, responses from around 9000 automobile users were gathered seeking socio-demographic information and overall satisfaction scores (ranging from 6 = excellent to 1 = worst). Accordingly, the parameters exerting significant ($p < 0.001$) influences on overall satisfaction were highlighted by Pearson's correlation analysis. Evidently, the arrangement of significant parameters comprised of six attributes. Exceptionally reliable, however less erratic Automobile Level of Service (*ALOS*) models were formulated considering these six variables with the assistance of a unique and widely used artificial intelligence technique in particular, Multi-Gene Genetic Programming (*MGGP*). The model displayed incredible likelihood efficiencies in the present article and delivered high coefficient of determination (R^2) of 0.875 under the prevalent conditions. The sensitivity analysis of demonstrated attributes showed that traffic volume per effective road width, effect of non-motorised vehicles and pavement condition index highly influenced the *ALOS* of signalised intersections in urban Indian context. The vital results of this work would, to a great extent, help the transportation organizers and architects in evaluating the operational efficiencies of signalised intersections and in making efficient resolutions for the better administration of automobile traffic.

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Keywords: Signalized Intersections; Automobile Users; Level of Service; Perception survey; Multi-Gene Genetic Programming

1. Introduction

The intricacies of traffic movement in Indian situation is fundamentally because of its heterogeneous attributes of the flow stream. Traffic stream in India comprises of motorised and non-motorised vehicles plying in a similar stretch with no proper lane discipline. This makes an intersection congested and results in inadequacy of wellbeing for vehicular and pedestrian movements primarily amid peak hours. Intersections are nodal focuses in a transportation

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network. They are common spaces which are shared by numerous approaches at any given moment. It is very critical to outline these intersections securely as they are the areas of most extreme conflicting centres and their efficiency of operation altogether impacts the execution of the whole system. Intersections can be signalized or unsignalised. Signalization is warranted to address road safety, effectiveness or operational issue or to enhance crossing opportunities for cyclists and people on foot. Signalized intersections are by and large introduced at convergences of significant or major streets and for the most part include numerous approach paths on every leg. Here, the common space is used in a substitute way by a given number of approaches for a time period which is defined beforehand, as outlined by the phasing plan implemented for the signalized intersection. At the end of the day, the same space is time-shared among the different traffic streams. There are different sorts of time sharing strategies like pre-timed, partially actuated and completely actuated signalizations. The evaluation of capacity and level of service (*LOS*) are the most extreme parts for performance assessment and for productive planning and outlining of a signalized intersection. Indeed, delay and queuing process are very crucial in the analysis and design of the signalized intersections for a particular *LOS*. The functional qualities of a signalized intersection are influenced by the magnitudes of vehicles and their arrangement alongside their coveted movements, geometric plan of the convergence and the signal attributes. These utilitarian qualities can be evaluated with a methodology of capacity, delay and performance analysis individually. Execution of a signalized intersection is exclusively in view of its *LOS* and even on the pattern of queue release alongside its headway qualities**.**

Automobile is the most overwhelming method of road transportation, which incorporates numerous vehicle classes, for instance, bikes, cars, *LCV*s, and auto-rickshaws, etc. Because of the huge increment in traffic thickness in the course of recent decades, transportation engineers are finding it incredibly difficult to give desirable comfort levels to the motorists. Though specialists have made a few endeavours to investigate the elements influencing operational qualities of drivers, yet, all these works generally consider homogeneous and lane based traffic conditions prevalent in developed nations as opposed to the Indian traffic flow condition which is quite complicated. Heterogeneity in traffic stream indicated by the presence of both slow and fast moving vehicles in the stream and no proper lane discipline with appropriate lateral movement at intersections complicate the Indian traffic scenario. These basic differences restrict the use of existing relationships of saturation flows and PCU factors for developing nations like India. Even no guidelines are available for estimating saturation flow for non-lane based heterogeneous traffic flow conditions. Consequently, new prediction models need to be developed for the developing nations instead of using the models devised for the developed nations.

In this respect, this examination has endeavoured to define the *ALOS* criteria through the inside and out examination of users' feelings on the current on-street riding condition. Therefore, the accompanying three noteworthy goals are achieved, which would generally help the transportation chairmen for dealing with the heterogeneous traffic in a better and more secure way:

- To identify the significant service attributes, affecting comfort level of drivers at signalised intersections in urban Indian context.
- To develop effective signalised intersections *ALOS* models using a popular soft computing technique namely, Multi-Gene Genetic Programming.
- To classify the Automobile drivers' level of satisfaction scores ($ALOS_{Overall}$ score) into six categories of *LOS* (A-F) for signalised intersections and identify the most efficient courses for the administration quality upgrades of signalized intersections in the urban localities.

2. Background Literatures

Several researchers, since the past few decades, have carried out extensive works regarding the performance assessment of signalized intersections based on user perception. Messer and Fambro (1975) presented a guide for designing and operating signalized intersections to serve peak hour traffic demands. These design criteria were mostly related to traffic operational measures which were more descriptive of the quality of traffic flow from the motorists' point of view along with some procedures for intersection signal timing and evaluation. Sutaria and Haynes (1977) carried out a user perception investigation to know drivers' opinions regarding *LOS* at intersections with signals. Delay was concluded to be the highly influencing factor and it connected well with *LOS* ranges. Ha and Berg (1995) conducted a research with an objective to cultivate a technique in order to evaluate *LOS* on the basis of safety at signalized intersections in connection with the comparative danger of substitute intersection designs and signal control methods. Pecheux et al. (2000) distinguished that *LOS* ranges based on delay at intersections with signals were not based straight away on surveys of user opinions. Zhang and Prevedouros (2003) followed *HCM* 2000 and developed a prototype to bring together delay and safety to obtain a widespread *LOS* indicator, that is, delay and safety index for signalized intersections. The suggested methodology modelled the trade-off between safety and efficiency clearly and included both inter-vehicle and vehicle-to-pedestrian clashes connected with left turns. Lin Zhang (2004) implemented the possible clash method and fuzzy set theory to find out *LOS* of intersection with signals which accounted for user opinions, the possible clash analysis technique, the fuzzy weighted average and the fuzzy logic technique. He found that delay needed to be complemented by several characteristics of signalized intersections in order to represent *LOS* that agreed better to road user opinions. Lee et al. (2007) devised a different methodology for assessing transportation service nature and facilities offered by signalized intersections utilizing fuzzy aggregation and a traditional consent analysis technique. Individual perceptions regarding the service quality of signalized intersections were evaluated by using a fuzzy weighted-average method on the selected six standards. Fang and Pecheux (2009) dealt with how users framed an idea about the superiority of service at signalized intersections and how many levels of services motorists were capable of perceiving. Zhang and Prevedouros (2011) presented a method basing on fuzzy logic in order to decide *LOS* of signalized intersections which clearly accounted for user opinions. Delay was considered as the significant and one and only standard for deciding *LOS* of signalized intersection.

In recent years, researchers are taking keen interest in studying the delays and queue lengths at signalized intersections in a rather explicit manner. Ban et al. (2009) studied methods to estimate intersection delay patterns by using measured travel times through which the researchers estimated the delay for any vehicle arriving at the intersection. The authors formulated the model using sampled travel times between two consecutive locations on arterial streets, one upstream and the other downstream of a signalized intersection. Chen et al. (2017) broadly studied urban arterial performance evaluation having principal attention on the determination of average commute time. The authors put forward a stochastic method that integrated definitive growing curves along with likelihood philosophies so as to inspect delay erraticism at signalized intersections. Saha et al. (2017) offered an improvised model for estimating delay at signalized intersections with the prevailing traffic flow conditions being highly heterogeneous since the prototypes established based on the homogeneous traffic conditions yielded inaccurate outcomes for developing nations where the traffic is extremely varied with practically no lane discipline.

Ban et al. (2011) studied the ways to find out real time queue lengths utilizing intersection travel times accumulated from mobile traffic sensors at signalized intersections. Chang et al. (2013) presented a simple procedure to calculate queue length on any approach of a signalized intersection. This methodology had a minimal set of data especially flow, occupancy, cycle length, and detector setback as compared to the existing techniques that relied on guessing vehicle courses using thorough data defined on per signal cycle basis. Cai et al. (2013) formulated a calculating method with zero initial queue by making use of information of floating cars and loops.

Truly, the nature of automobile activities near signalized intersections are influenced by different geometrical, traffic and in-built environmental elements. Besides, the apparent satisfaction levels of drivers with diverse age grouping, sexual orientation, driving knowledge, and so forth., are too profoundly prone to be unique in relation to each other. In this manner, it is required to define the signalized intersection *LOS* in urban Indian context considering all these factors. In light of this, the present work has attempted an inside and out investigation of all the variables influencing *ALOS* at signalized intersections. Along with different quantitative properties, the importance and essentiality of social, demographic and travel attributes of motorists are additionally researched. In this way, the essential traits are identified, and the *ALOS* model is formulated using *MGGP*. Performance of this model is tried with broad datasets and outcomes are deciphered.

3. Study Methodologies and Applied Artificial Intelligence (*AI*) Technique

After developing an idea regarding all the parameters and attributes which may possibly influence the *LOS* of signalized intersections, a suitable study area is selected and all the available traffic, geometric and in-built environmental variables are collected. By performing the significance test using Pearson correlation, the significant attributes are finalized. However, all these significant attributes are not primary as they cannot be obtained directly from the field. Some of them are quite complex in nature (secondary). These variables are basically control delay and queue length at the signalized intersections. The methodologies which lay down the platform for estimation of control delay and queue length at the signalized intersections are vividly described below as these processes are quite tiring and cumbersome. Then, suitable techniques are employed to model these attributes followed by validation of the model and sensitivity analysis. The methodological framework of the study has been shown in Fig. 1.

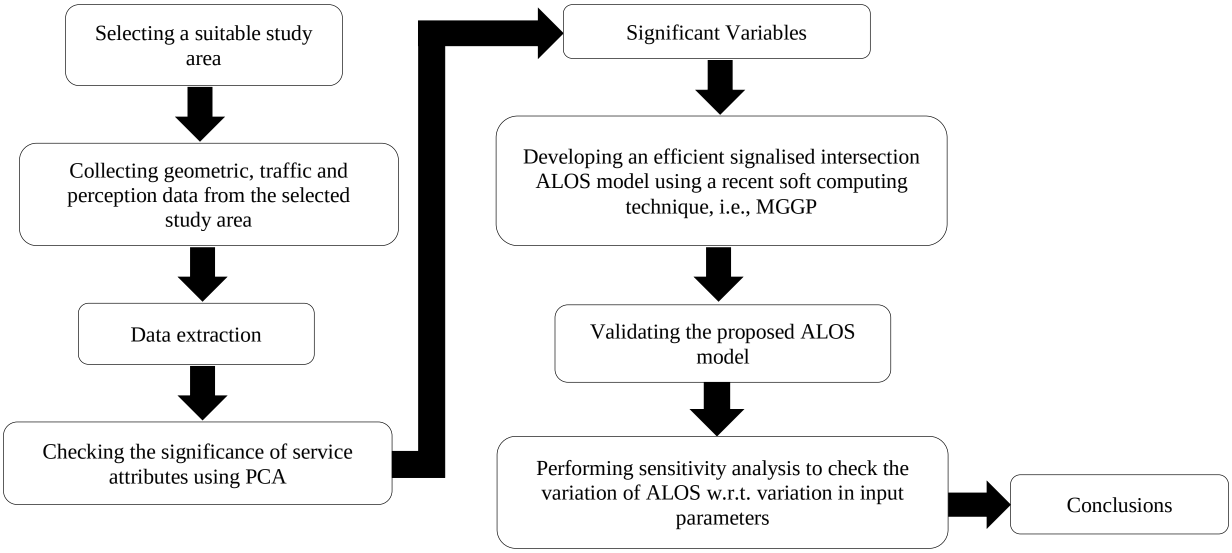


Fig. 1. Stepwise procedure of the research work

3.1 Control delay estimation at signalized intersections

The quality of traffic operation is mostly determined by delay. While delay measurement directly from the field is possible, yet, it is a quite tedious process. Since, delay at a signalised intersection constitutes a major part of travel time, its estimation is quite necessary. Earlier, average stopped delay was suggested by *HCM* 2000 for determining *LOS* at signalised intersections. However, *HCM* 2010 recommends the use of average control delay as the single measuring standard for estimating *LOS* of signalised intersections. Average control delay of both major-street and minor-street are generally considered for formulating *ALOS* models at signalised intersections. Control delay is a portion of total delay that results from the type of control at the intersection. It is measured by comparing it with the uncontrolled condition. It is the difference between the travel time that would have occurred in the absence of the intersection control and the travel time that results because of the presence of the intersection control (*HCM* 2010). The control delay comprises of three main components, namely, uniform stop delay, oversaturation or incremental delay and the stopped delay caused by initial queue gathered behind the intersection from previous cycles.

From the background literatures related to delays at signalized intersections, cycle length, green ratio(E_g/C) and volume to capacity (v/c) ratio are found to significantly influence control delay at the intersections. Besides these factors, other factors like inter green time, number of phases, number of lanes as well as left turn on red at an intersection do have a noticeable effect on control delay. *HCM* method or Webster Delay model which consider homogeneous traffic flow conditions is the basis of most of the delay based studies at signalized intersections. However, Saha *et al.* (2017) have proposed a more accurate and justifiable mathematical method for estimating control delay under heterogeneous traffic condition taking into account the effect of all the above mentioned parameters. The proposed delay model comprises of three components:

$$d = d_1 + d_2 + d_3 \tag{1}$$

Where,

- d_1 is the uniform delay of vehicles entering into an intersection and is a function of cycle length (*C*), volume-capacity ratio (*X*) and green ratio (E_g/C) as shown in Eqn. (2).

$$d_1 = \frac{0.5 \times C \times (1 - \frac{E_g}{C})^2}{(1 - X \times \frac{E_g}{C})} \tag{2}$$

Here,

C is the cycle length in seconds.

g is the effective green time in seconds.

X is the degree of saturation (*v/c*)

v is flow rate i.e., the average number of vehicles passing a given point on the road in the same direction per second.

c capacity for the lane group in vehicles per second.

All the parameters considered in estimating the uniform delay have been extracted either from the videos or are directly collected or recorded from the field.

- d_2 accommodates the variation in the arrival of vehicle platoons at different points of signal cycle and especially during green time. This relationship between incremental delay (d_2) and arrival pattern of platoons is depicted by performing regression analysis according to which

$$d_2 = 6.23 - 15.35 \times R_p \tag{3}$$

R_p is the Platoon ratio and is given by the ratio of percentage of vehicles arriving during green to percentage of green time.

- d_3 is zero here as no vehicles are left after the cycle is completed.

Hence, mathematically, the control delay at signalised intersections is calculated using Eqn. (4).

$$d = 6.23 + \frac{0.5 \times C \times (1 - \frac{E_g}{C})^2}{(1 - X \times \frac{E_g}{C})} - 15.35 \times R_p \tag{4}$$

3.1.1 Platoon ratio for control delay estimation at signalized intersections

Platoon ratio is used to describe the quality of signal progression. It is computed as the ratio of demand flow rate during the green signal indication to the average demand flow rate. The values of platoon ratio lie between 0.33 to 2.0. The platoon ratio can be calculated from the field data using Eqn. (5).

$$R_p = \frac{P}{E_g / C} \tag{5}$$

Where,

R_p = Platoon Ratio

P = Proportion of vehicles arriving during the green indication (in decimal)

E_g = Effective green time (in seconds)

C = Cycle length (in seconds)

The proportion of vehicles arriving during the green indication, P, is considered as the ratio of number of vehicles that arrive during the green indication to the count of vehicles that arrive during the entire signal cycle. It is an average value representing conditions during the analysis period. Platoon ratio is calculated by extracting the data from the videos. First of all, for a given approach, the number of vehicles arriving during green are counted. This is expressed as a proportion of the total number of vehicles moving in that approach in the complete cycle. Secondly, the green time of that particular approach is expressed as a proportion of the cycle length. Then, these two values are divided to obtain the platoon ratio.

3.2 Queue length estimation at signalized intersections

Queuing is the study of traffic behaviour near a certain section where demand exceeds available capacity of carriageway to accommodate traffic volume. Queuing can occur at red lights, stop signs, bottlenecks, or any design-based or traffic-based flow constriction. When not dealt with properly, queues can result in severe network congestion or "gridlock" conditions. As suggested by *HCM* (2010), Queue length (Q_l) is the distance of the vehicle stopped farthest from the STOP line during the cycle as a result of the display of a red signal indication. The back-of-queue size depends on the arrival pattern of vehicles and on the number of vehicles that do not clear the intersection during the previous cycle.

For estimating queue length on any selected approach, a longitudinal trap is considered on it. The trap is extended from stop line of the intersection to the end of the queue in order to mark the entry and exit of vehicles at the intersection. Entry of a vehicle into the trap marks its entry time. Similarly, when the vehicle completely crosses the STOP line, it demarcates the exit time of that vehicle. All the vehicles entering and leaving the trap are considered for queue length estimation. Queue lengths are finally decided through rough eye estimation in a few randomly selected cycles. On a specific note, queue lengths for a particular approach of an intersection are expressed in terms of number of vehicles previously standing in a queue along with those just arriving within a five seconds interval, excluding those that have already crossed the STOP line during that time period (*HCM* 2010).

3.3 Modelling with Multi-Gene Genetic Programming (MGGP) technique

Although statistical modelling strategies such as regression are to a great extent utilized for the improvement of administration forecast models, *AI*-based models have numerous preferences. Applying soft computing techniques for model building is quite advantageous in the way that they even solve nonlinear problems, in which mathematical models are not available and they introduce the human knowledge like cognition, recognition, understanding, learning, and others into the fields of computing. Soft computing techniques are capable of tolerating imprecision, uncertainty, and partial truth to achieve tractability and robustness on simulating human decision-making behaviour with low cost. It provides a platform to represent ambiguity in human thinking with the uncertainty in real life. Here, the model structure need not be specified a priori. Soft computing methods can approximate complex nonlinear and dynamic systems. Moreover, they can construct or perceive "Linguistic Variables" and can formulate rules and equations. Consequently, the current work has managed the advancement of *MGGP* based *ALOS* model which is as of late presented and are not extremely basic to the transportation designing experts. Thus, the basic idea behind this approach is briefly exhibited underneath for better understanding.

MGGP is an extension of Genetic Programming (*GP*) which is used to develop a mathematical model that is empirical in nature between output and inputs. It is also known as symbolic regression. The primary inspiration of utilizing *MGGP* strategy is that it creates exceptionally compacted prescient conditions, which is not really conceivable while utilizing numerous other *AI* strategies. *MGGP* is regularly known as the gray-box arrangement of prescient models. It coordinates the demonstrating capacities of *GP* method with the regression analysis. Accordingly, *MGGP* is known as an effective variation of *GP*. Its developmental mechanism takes after the standards of *GP* procedure. It naturally advances computer programs to create prescient models without indicating their structures in advance. This standard has made *MGGP* approach surprisingly worthwhile over different statistical techniques. Once the initial populace is ready, the objective function surveys the forecast capacity of each parental quality and returns a fitness value for it. In the current workspace, the root mean-square error (*RMSE*) of observed and anticipated estimations of the yield variable is utilized as the goal work or the objective function. Unless the issue is so little and straightforward, the greater part of the initial genes shows extraordinary poor fitness esteems. Consequently, *GP* makes a posterity populace of better-fitted people by executing different hereditary administrators (reproduction, crossover, and mutation) on the initial genes. This progression is known as generation-1. In the propagation or reproduction process, better-performing people of the underlying population are straightforwardly duplicated to the posterity populace. In the crossover process, better-performing posterity qualities are made by trading the subtrees of any two parental qualities or genes chosen in extent to their fitness value. In the mutation process, a haphazardly chosen node of the parent is supplanted with a component of the terminal set. Here, the functional node is supplanted with a functional element and the terminal node is supplanted with a terminal component or element.

MGGP utilizes mathematical functions to set up the best configuration of input variables for the expectation of the yield variable with high exactness. These mathematical functions do different blends as well as changes of the input variables to make them very efficient for the forecast of model yield. At generation-1, the recently generated posterity populace replaces the underlying one. The posterity populace again experiences the hereditary activities to make another populace of better-fitted posterity people (generation-2). This iterative procedure proceeds over numerous generations and ends when either the threshold fitness value or the greatest of the number of generations is accomplished. Consequently, the best-fit individual showed up at any generation defines the yield of the GP formalism. The *MGGP* formalism is additionally done in comparative way with the exception of that, every individual in *MGGP* is a linear amalgamation of at least two trees of *GP* associated with weights, which are alluded as 'genes'. Therefore, this extemporized procedure is named as multi-gene *GP* or *MGGP*. The combination of two or more genes (g) occurs as follows to estimate the output variable (y):

$$y = a_0 + \sum_{j=1}^{n} a_j g_j = a_0 + \sum_{j=1}^{n} a_j \times F[X, f^{'}(X)] \tag{6}$$

Where,

a_0 is the bias parameter, n represents the number of genes (g) in the target expression, a_j is the weight or linear coefficient of jth gene ($g_j = F\ [X, f'\ (X)]$), F represents the model function, X represents the vector of influencing variables, and f' is a functional element selected from the functional set. In MGGP, a_j and a_0 parameters are estimated by using the ordinary least squares method, i.e., by minimizing the sum of squared errors between actual and predicted 0 outputs.

3.3.1 Execution procedure of MGGP technique

GPTIPS is the genetic programming tool for use with *MATLAB*. *GPTIPS* provides a number of convenient functions for exploring the population of evolved models, investigating model behaviour, post-run model simplification and export to different formats. One of the main features of *GPTIPS* is that it can be configured to evolve multigene individuals. This feature can be used to create simpler and more accurate models. Firstly, out of the four symbolic regression demos included with *GPTIPS*, *GP*demo2 is selected which runs multigene *GP* symbolic regression on a data set generated from a non-linear mathematical function comprising one output and more than one inputs. Both testing & training data are noise free. In addition to the *GP*demo2 file, a *GP*demo2 configuration file is run simultaneously where various inputs are set. These inputs include population size, number of generations, run information such as best fitness, mean fitness and best node count to be displayed on screen after how many generations, method of selection size of the selection, fitness function specifications, input configuration, maximum tree depth, multiple gene settings together with the definition of various functions like 'plus', 'minus', 'sin', 'cos', etc. A particular function is considered active in the program if its value is set '1' and is considered inactive if set '0'. Along with these inputs, a *MATLAB* file is created through which x and y values of training and testing data are individually fed to the code. The population size is fixed at 1000, run information is to be displayed on screen after 10 generations. Tournament selection is adopted as the method of selection, number of inputs is fixed at 6 and all the functions are kept active. Besides these inputs, all other input parameters are changed after every iteration in order to reach at the desired value. The code is run and several trials are considered and finally, the model could explain a wide variation when number of generations is fixed at 150, tournament size is kept as 5, fitness function termination criterion is kept at 0.0001, maximum tree depth is considered as 4 and a maximum of 5 genes are considered. Using the symbolic math tool box it is possible to combine the gene expressions with the gene weights (regression coefficients) to display a single function that predicted the output using the inputs $x_1, x_2, x_3, x_4, x_5, x_6$. Finally, the technique highlights the best among all the models in the population.

4. Study Area and Data Collection

The gathering of sufficient measure of information from diversified intersections is the essential prerequisite for building up an all-around summed up *ALOS* model. In-situ investigations, videotaping and surveys based on perception are conducted in order to cluster the data sets (such as geometrics of the intersection, traffic volume parameters, cycle length, quality of the pavement, in-built environmental details etc.) required for *ALOS* model development.

India, being a country which exhibits diversity or heterogeneity in all its spheres, the first and the foremost criterion for selection of the study area is that the area should be such that it represents a Mini-India within itself. The area should rightly portray the heterogeneity in all types of traffic flow conditions. As a result, the developed model can be universally applicable to the entire country. The area should not impose any kind of obstructions to data collection. All the selected parameters which need to be collected from the area should be easily accessible. It is desirable if the area can support with a large quantity of data sets. This will be a great help in the model development process. Keeping in mind all these criteria, Kolkata city of West Bengal has been aptly selected for the study purpose. Its geographical location has been shown in Fig. 2.

Fig. 2. India Map showing the study area

Kolkata, also known as the ‘city of joy’ is the principal commercial, cultural and educational centre of East India. It expands over an area of 205km^2. It houses some premiere educational institutes and universities and moreover, we can’t deny the fact that Kolkata is an IT hub. Because of this reason, we find a huge range of variation in demographics of human population. As a result, the sample which we considered for our research purpose is representative of the diversified population here. Recent estimates make it the third most productive metropolitan area in India, after Mumbai and Delhi. Public transport is provided by the Kolkata Suburban Railway, the Kolkata Metro, trams and buses. The Port of Kolkata is India’s oldest operating port and its sole major riverine port According to 2013 study carried out by International Association of Public Transport, Kolkata is at the topmost position among the six cities studied in India, in the form of public transport system. Kolkata has 4 long-distance railway stations and Netaji Subhash Chandra Bose International Airport, located in Dumdum some 16 km north-east of the city centre which operates domestic and international flights. The city serves as the headquarters of three railway zones out of 17 of the Indian Railways regional divisions. The Kolkata-Delhi and Kolkata-Chennai prongs of the Golden Quadrilateral and NH34 start from the city. It is also found that NH 2 and NH 34 are intersecting with NH 6 here.

In a group, a total of 45 signalized intersections are inspected in the present study. Among all, 34 are 4-legged intersections and the remaining 11 are 3-legged or T-shaped intersections and all these intersections have actuated and semi- actuated traffic signals. The roads connecting to the intersections from both major and minor leg include mainly 3 lanes and occasionally 2 lanes approach. Wherein, roads differ in terms of geometric parameters, traffic parameters, in-built parameters with heterogeneous types of vehicles moving on the road. The road conditions in all the cases range from being very good to average. In most cases, the road approaching the intersection has proper road markings.

5. Data Collection and Extraction

From the extensive literature survey, information regarding all those feasible parameters considered in previous works is gathered. Along with it, their relative significance in the model is also studied as incorporating every single variable in the study would be quite cumbersome. There are two kinds of variables collected from the field: Quantitative variables which include all the geometric, traffic flow and built-environmental parameters and Qualitative variables. For every facility which is being designed or made available for use, public is the main customer. They actually rate the success of the facility. Hence, their opinions need to be recorded. Therefore, perception study is undertaken to record the overall satisfaction of the drivers with the available facilities. Different parameters identified with geometrics, operational behaviour of traffic and in-built ecological conditions are outlined, which may have significant influences on the *ALOS*. An elaborate discourse of each one of these variables alongside their collection and extraction techniques is presented below.

5.1 Quantitative variables

Video recording was thought of as the simplest way for the purpose of data collection from signalised intersections. Two high resolution cameras fitted over tripod stands served the purpose of video recording mostly at peak hour of traffic. Morning peak and evening peak hours were generally considered while recording videos in order to study the peak hour traffic flow variation at several intersections. High elevation points were chosen so that every leg of an intersection could be clearly captured by the camera, whether three or four-legged. In cases where such points were unavailable, two cameras were set up at road level on either side, i.e., upstream and downstream side of the studied intersection thereby, covering all the legs of the intersection. The camera placed on the upstream side of the studied approach records vehicle arrival rate as well as signal timings while the other placed on the downstream side of the approach recorded departure rate of the vehicles passing through the intersection. Measuring tape was used for noting down the carriageway width, shoulder width and median width if present.

5.1.1 Collection and extraction of traffic flow variables

Parameters like traffic volume in each approach, capacity, control delay, queue length effective green time, red clearance, amber time, cycle length, percentage of vehicles arriving on effective green and on street pedestrian volume came under the sub-heading of traffic flow variables.

- Data regarding traffic volume in each approach were collected by installing two video cameras on opposite legs of the intersection so that all the legs are properly visible. The traffic volume included flow of main road and cross road. Volumes of motorized and non-motorized vehicles were determined. All the vehicles were converted into the standard passenger car by multiplying the suitable PCU equivalents with the respective types of vehicles as prescribed by IRC-106(1990). Then, for a particular approach, these values were added up to give the hourly total traffic volume of that approach in PCUs/hr. Since, under mixed traffic conditions, arrival/departure rates might vary depending upon the traffic composition, considering constant arrival and departure rate of vehicles was practically incorrect. At certain points of time, it was found that the flow was very high (fully saturated) while at times the flow was found to be quite low (under saturated). As a result, the peak 15-minutes period traffic flow within the hour, being the most critical one, was taken into consideration. These values were multiplied by a constant factor in order to express the flow values in terms of PCUs/hr. Of all the approaches, only through traffic was considered for the further analysis.
- Capacity (c) is the maximum flow on a road section considered at saturation flow condition and is expressed in vehicles per seconds. Capacity related information was estimated by collecting the arrival and departure videos which were recorded using high resolution video cameras installed at upstream and downstream side of the signalised intersections. The duration of the green up to which there were at least three vehicles to discharge was taken as the effective green time. The total number of vehicles crossing the intersection during saturated green time was considered as the saturation flow rate. The reason for taking three vehicles in the queue was due to the mixed nature of traffic and abreast movement of vehicles. Capacity of each approach was determined by playing the videos of arrival and departure which were recorded at the signalised intersections.
- Control delay data for each approach was not collected directly from the field. It was calculated using a very recently developed delay model proposed by Saha et al. (2017) for heterogeneous traffic conditions. The other parameters required for delay calculation were first collected, extracted and then, control delay at intersections was estimated. It was expressed in seconds.
- Data regarding queue length of each approach were collected by manually counting the number of vehicles entering and leaving the longitudinal trap at the intersections. These were the vehicles standing in a queue to pass the intersections. It was expressed in number of PCUs.
- Effective green time (E_g) is the time during which a given traffic movement or set of movements may proceed at saturation flow rate. It is the time for which a particular stream can utilise the intersection. Amber time interval is to warn the traffic of an impending change in the right-of-way assignment. It is a warning signal. Red clearance interval is the interval that follows a yellow change interval and precedes the next conflicting green interval. It is intended to provide additional time following the amber change interval to clear the intersection before the conflicting traffic is released. Effective green time data for each approach were either calculated from the digital timer displays available at certain signalised intersections or by using a stopwatch. Amber time and red clearance for each approach were also directly collected from the site by using stop watch. All the three parameters were expressed in seconds.
- Cycle length (C) is the time that it takes a signal to complete one full cycle of indications. It indicates the time interval between the starting of green for one approach till the next time the green for that approach starts. Cycle length was obtained by adding the effective green, amber and all red time. It was also expressed in seconds.
- Data regarding percentage of vehicles arriving on effective green and on-street pedestrian volume were collected by installing video cameras on the opposite legs of the intersection. Proportion of vehicles arriving on effective green was extracted for all the cycles by playing the videos of both arrival and departure. It was expressed in PCUs/hr. On street pedestrian volume was extracted by counting the number of pedestrians crossing the intersection from the video and expressing it in terms of number of pedestrians per hour.

5.1.2 Collection and extraction of roadway geometrics and other road conditions

Roadway characteristics comprised of lane width, carriageway width, number of intersection legs and lanes, presence of median and pavement quality.

- Data regarding lane width of each lane and carriageway width were collected directly from the site by measuring the width of the lane and carriageway with the help of a measuring tape and recording it. Lane widths and carriageway widths were expressed in metres.
- Number of intersection legs and lanes were counted manually and expressed in number.
- Data for presence or absence of median on each intersection leg were collected by visual observation and then recording the same. Presence of median was denoted as 1 and its absence as 0.
- Other road conditions like pavement quality was quantitatively expressed as Pavement Condition Index (PCI) on a five-point scale where 1 signified the worst condition and 5 signified the best one. PCI values were decided based on eye estimation.

5.1.3 Collection and extraction of in-built environmental parameters

All kinds of built-environmental parameters included effect of heavy vehicles, effect of non-motorised vehicles, on-street parking density, roadside commercial density and obstructions due to encounters.

- Data corresponding to number of heavy vehicles for each approach were collected through videography. It was extracted from the videos and expressed as a percentage of the total traffic in each corresponding approach.
- Similarly, data pertaining to number of non-motorised vehicles for each approach were also collected through videography. It was extracted and expressed as a percentage of the total traffic in each corresponding approach.
- On-street parking density data for each approach were collected using video cameras and extracted by literally counting the number of vehicles parked in and around the intersections observed from the videos and then, it was expressed as a percentage of the total volume in each respective approach. The parking densities were classified into four sub-divisions namely, absent/low, medium and high based on the percentage of parked vehicles.
- Roadside commercial density data for each approach were collected visualising the number of centres at or near the intersection where commercial activities were taking place. Based on the commercial establishments available near the intersections, on-street commercial density for each approach was classified again into absent/low, medium and high. This was done by playing the videos of each intersection.
- Lastly, obstructions due to encounters data for each approach were collected by using a stopwatch to note the average time interval to face an encounter.

Suitable adjustment factors were assigned to incorporate the effect of each of the aforementioned variable into the study. These adjustment factors were proposed by Jena et al. (2018).

5.2 Perception survey of automobile users

While evaluating any facility, it is quite important to include the opinions of those using the facility. Users' level of satisfaction helps in developing the idea regarding the extent to which they are happy with the facility or vice-versa. This, in turn, helps in incorporating the necessary changes required to improve a particular facility. HCM does not take into account how the users perceive any facility. As a result, the models don't seem to be realistic. Face to face interviews of the various automobile users are taken to analyse their perceived ALOS scores on each approach of the intersections. A total of 9000 responses have been collected from all the intersections in a whole. Out of it, 150 responses are incomplete and hence, discarded from the study. This survey consists of socio-demographic and other information of the participants along with their overall satisfaction ratings of the facility.

5.2.1 Demographics and other information

A questionnaire was prepared where various information on socio-demographic and travel pattern of the automobile users were recorded. These included information about their age, sex, educational background, driving experience, employment status, type of vehicles, frequency of using the intersection etc. This information was summarised in a tabular manner and presented below. The main aim behind gathering so much information was to include the responses from each section of the diverse population. This would justify the diversification of Indian population and hence, the universal applicability of the model. Participants who registered their opinions were generally users of bikes, cars, LCVs, auto-rickshaws, buses etc.

5.2.2 Overall satisfaction scores

Along with the demographics and other personal information, the generated questionnaire was also used to seek information regarding the extent to which the automobile users were satisfied with the smoothness of the riding surface, comfort and safety offered by the facility. Respondents were thoroughly explained regarding the main motive behind the study. The automobile drivers were asked to give their ratings immediately after crossing the intersection. They were either asked verbally to rate the facility according to their level of satisfaction or they gave their responses in the forms provided to them. These overall satisfaction scores were expressed on a six-point scale (1, being highly dissatisfied and 6, being highly satisfied).

Table 1. Demographic information of survey respondents.

Attributes	Distributions	Percentages
Gender	Male	53
	Female	47
Age	18-25 years	39
	26-40 ears	35
	>40 years	26
Educational Background	Proper	85
	Poor	15
Driving Experience	2-5 years	20
	5-15 years	48
	>15 years	32
Employment Status	Employed	87
	Unemployed	13
Type of vehicles	Bikes/Two-wheelers	28
	Cars	18
	LCVs	30
	Autos	8
	Buses	16
Frequency of using the intersection	Often	90
	Less frequently	10
Total Respondents		100

6. Results and Analysis

The preparatory advance of model development includes the choice of different autonomous factors or variables, which exert a significant influence on the dependent variable. The factors having insignificant influences on the reliant variable are not considered for the model development. The conceivable arrangement of independent factors for the present issue incorporates signalized intersection physiognomies and automobile users' attributes. Then again, the arrangement of dependent variables incorporates apparent *ALOS* scores. Therefore, the underlying database included 9000 perceptions altogether (i.e., 200 perceptions for every one of 45 signalized intersections).

6.1 Variables selection based on significance test

Both continuous and ordinal (or hierarchial) sorts of factors or variables are contained in the database. For example, traffic volume, traffic speed, queue length, control delay, carriageway width, effective green, red clearance and cycle length are continuous factors, while encompassing commercial density, pavement condition index, on-street parking manoeuvre, effects of heavy and non-motorised vehicles, obstructions due to encounters and apparent ALOS scores are ordinal. Thus, the Pearson's correlation analysis is favoured for the identification of significant factors as it is well fit for managing both consistent and ordinal kinds of factors. Pearson's correlation coefficient (i.e., Pearson's r) is evaluated for every independent variable versus the dependent variable, and its significance (*p*-value) is tried.

6.1.1 Significance of quantifiable roadway elements, traffic flow and other parameters

The greater part of the quantitative factors gathered in this investigation are incorporated into the Pearson's correlation analysis. The factors listed below are seen to have significant and free influences on the apparent *ALOS* scores: Peak hour traffic volume per path width (*v/w*), control delay (*d*), queue length (Q_l), pavement condition index(*PCI*), factor representing the rate of non-motorised vehicles (N_v) and factor representing the impediments or hindrances caused because of encounters (E_n). It is to be noticed that, if at least two significant factors are exceedingly related with each other (r = 0.8), they are multi-collinear. For this situation, the variable having the most astounding connection with yield variable is chosen for model building, and others are dropped from further contemplations. These factors have been gathered from broadly diversified street conditions existing in urban chunks of developing nations. Along these lines, the database is appropriate to formulate well generalised *ALOS* models. A positive estimation of Pearson's r shows that the estimation of yield variable increases with the increase in the estimation of the concerned input, while a negative estimation of the same demonstrates the switch. Table 2 shows the results of the significance test where out of 21 variables selected for the study, only six are significant at 95% confidence interval level. Along with this, the table also shows the correlation of all independent variables with the dependent variable. With this hypothesis, it can be inferred from Table 5.1 that *ALOS* score increments just with the increase in estimations of *PCI*. On the other hand, *ALOS* score diminishes with increment in estimations of v/w, queue length, control delay, N_v and E_n. It is the assumption of this study that, a higher *ALOS* score assigns best service quality, and a lower ALOS score assigns the most exceedingly bad one. In this way, *v/w*, queue length, control delay, N_v and E_n adversely influence the operational efficiency of signalized road sections, while *PCI* positively influences the same. Table 3 shows the correlations between the independent variables. From the table, it can be deciphered that all the correlations are within a value 0.6 which is less than 0.8. Hence, no instance of multi-collinearity is observed in this study. The higher the correlation value, the greater is the affinity between the variables, this means the variation is exactly the same by magnitude. The maximum correlation can be observed between Q_l and d and the value is 0.54 and the second higher correlation exists between Q_l and *v/w* and the magnitude is 0.516. Both the correlations are positive in nature which indicates that they vary directly.

6.1.2 Significance of automobile drivers' attributes

Factors identified with the socio-demographic and travel characteristic for automobile users are subjective in nature. In this way, appropriate ordinal or hierarchical scales are defined to fuse these factors into the statistical analysis process. For example, the sexual orientation is inputted as '0' for females and '1' for males. Age is inputted as 1 for youth, 2 for middle age, and 3 for senior age. The driving background of automobile users is inputted as 1 for under 5 years, 2 for 5– 15 years, and 3 for over 15 years. Proper educational background of automobile users is inputted as 1 while those having a poor background are assigned 0. Employed users are assigned a value 1 while the unemployed ones are assigned 0. The automobile users using the intersection frequently are inputted as 1 and those using occasionally are inputted as 0. Among different attributes of automobile users, no factor is observed to be factually significant ($p < 0.001$). Although all the previously mentioned attributes of the automobile users change the estimations of perceived *ALOS* scores to some degree, those influences are not factually significant at the level of $p < 0.001$. Along these lines, each one of those parameters are dropped from the model building process.

6.1.3 Significance of the output variable

The Pearson's connection analyses discover that no members' trademark/characteristic significantly influence the apparent *ALOS*. In this manner, the $ALOS_{Overall}$ score attained for each approach of the signalised intersection is utilized as the yield variable. Thus, the initial database of 9000 observations which include all the approaches of all the 45 signalised intersections is reduced to 178 observations in total which include only the through movements or approaches for carrying out the analysis. Similarly, perceptions of only those automobile users are considered which form a portion of the through traffic.

Table 2. Correlation coefficients of input variables w.r.t output variable and their significances.

Correlations							
Variables	*ALOS*	*v/w*	*d*	*PCI*	Q_l	N_v	E_n
Pearson Correlation	1.000	-0.620	-0.500	0.482	-0.471	-0.375	-0.397
Sig. (1-tailed)	0.000	0.000	0.000	0.000	0.000	0.000	0.000
N	178	178	178	178	178	178	178

Correlations are significant at 0.05 level (1-tailed)

Table 3. Correlations among input parameters.

Variables	*v/w*	*d*	*PCI*	Q_l	N_v	E_n
v/w	1.000	0.407	-0.301	0.516	-0.055	0.403
d	0.407	1.000	0.019	0.540	0.141	0.319
PCI	-0.301	0.019	1.000	-0.105	-0.104	-0.061
Q_l	0.516	0.540	-0.105	1.000	-0.115	0.260
N_v	-0.055	0.141	-0.104	-0.115	1.000	-0.108
E_n	0.403	0.319	-0.061	0.260	-0.108	1.000

6.2 ALOS model development

Of the aggregate 178 observations (only through movements) contained in the final database, 70% (124 observations) were utilized for model training, and the remaining 30% (54 observations) were utilized for the model testing. The aggregate database was split into training and testing data sets such that the two data sets secured the extensive variety of every factor and represented comparable statistical properties. The values of the input and the output variables taken from the field are normalised in the range [0, 1] to avoid the dimensional effects of field observed values in the process of model building. Results acquired from the training and testing of MGGP model are elaborated below.

6.2.1 Development of MGGP based ALOS model

In the current study, the *MGGP* algorithm is executed utilizing *MATLAB* to evaluate the model parameters (a_j and a_0). The best *ALOS* prototype demonstrate for the present study was acquired with, a populace size of 1000 at 150 generations, g_{max}, D_{max}, p_r, p_c and p_m values of 5, 5, 0.02, 0.84 and 0.14 individually. Fig. 3 demonstrates the final populace of the *MGGP* run achieved for the problem defined in the present context. It demonstrates two arrangements of *ALOS* models through green-and blue shaded specks or dots. Here, the green dots are the arrangement of non-dominated models (better-performing or superior models), and the blue dots are the arrangement of dominating ones (inferior models). The curve of non-overwhelmed models is called as the "Pareto front". Along these lines, each point on the Pareto front signifies the present issue from which the best one is to be chosen. All models on the Pareto front predominantly differ from each other regarding their likelihood capacities and expressional complexities. The location of the best model on the Pareto front is demonstrated utilizing an arrow (Fig. 3). The best *MGGP* model was made out of five genes. Every gene is an element of certain arrangement of input factors. Consequently, the fundamental difference between these genes is that they exhibit various nonlinear alterations of a specific set of factors. Presenting the structures of individual genes, their scientific articulations are determined as under:

Gene-1= $7.574*x_1-3.787*x_2-3.787*x_3-3.787*x_4-3.787*(x_5)^4-3.787*(x_5)^2+0.9045$

Gene-2= $-1.126*x_6$

Gene-3= $4.074*x_3+8.148*(x_5)^2+3.71$

Gene-4= $-11.34*x_1-11.34*(x_5)^6$

and Gene-5= $3.758*x_1+3.758*x_2+3.758*x_4-3.758*x_5-3.758*(x_5)^6$

These genes don't represent an *ALOS* model individually, rather each one of them are joined together based on Eq. (6) to build an *ALOS* model. Specifically, the mathematical formulations of individual genes were multiplied with their comparing weighs and acquired outcomes were summed up with the bias term to develop the final *ALOS* model. The estimations of the bias term (a_0) and weights of five qualities (a_1, a_2, a_3, a_4 and a_5) were evaluated at 95% confidence level ($p < 0.05$) and the acquired outcomes are exhibited in Fig. 4. Statistical significances (p-values) of these coefficients are introduced in Fig. 4. As seen, the most astounding p-esteem is found for gene-2, which is under 1.5 ×10-5. Incorporating all these genes in Eq. (6), the mathematical interpretation of the *MGGP*-based *ALOS* model is inferred and exhibited in Eq. (7). This model would help the transportation organizers and designers in evaluating the $ALOS_{Overall}$ scores of urban signalized intersections working under heterogeneous traffic flow conditions with high efficiency and a little computational exertion.

$$ALOS_{Overall} = 0.287x_3 - 0.029x_2 - 0.008x_1 - 0.029x_4 - 3.758x_5 - 1.126x_6 - 3.787(x_5)^4 - 15.1(x_5)^6 + 4.361(x_5)^2 + 4.615 \qquad (7)$$

The R^2-values acquired between the anticipated and observed estimations of *ALOS* scores individually for training and testing datasets are automatically generated on running the code for *MGGP* and they are exhibited in Fig. 5 (a) and (b).

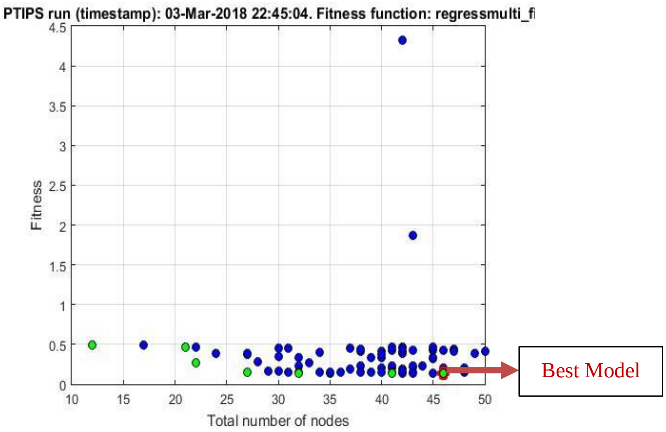


Fig. 3 Population of evolved models in terms of their complexities and fitness along with the best model

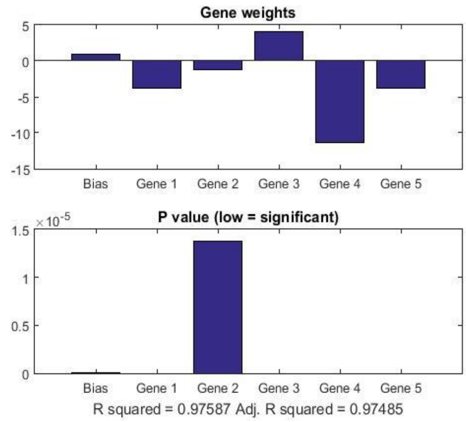


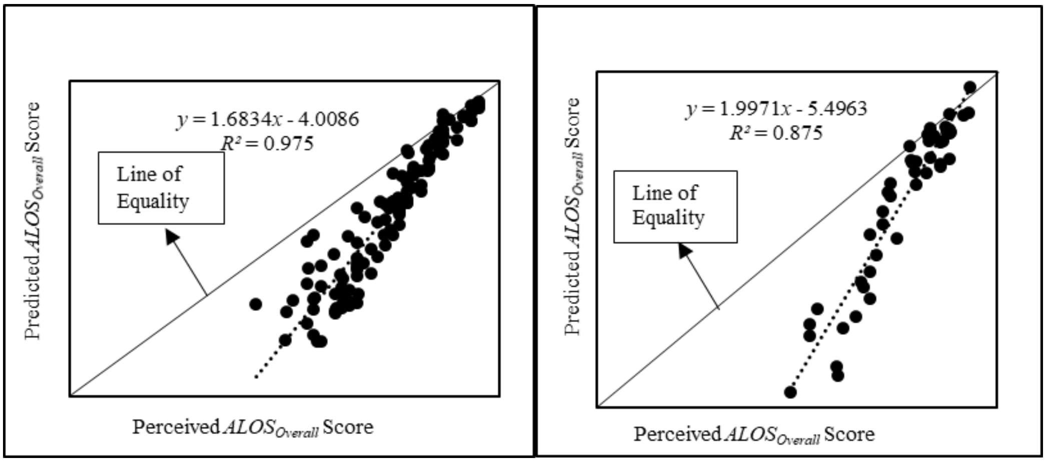
Fig. 4 *MGGP* based *ALOS* model showing gene weights (coefficients) and p-values (significances)

6.3 Model appliction

In this section, an example problem has been discussed to help in understanding the genuine implementation of the suggested ALOS model in the field. The followings are the observations collected from the field for one-side through movement of an approach of Behala Chowrasta Crossing. They are: v/w = 199.0286 PCU/h/lane, d = 8.35 seconds, PCI = 3, Q_l = 11PCUs, N_v = 0 and E_n = 0.1. The observed $ALOS_{Overall}$ score obtained from the field is 2.3. Similarly, the observations for the other side through movement of the same approach are: V/W = 170.8571 PCU/h/lane, d = 7.56 seconds, PCI = 3, Q_l = 12 PCUs, N_v = 0 and E_n = 0.1. The observed *ALOS* score obtained from the field is 3.02. Hence, the $ALOS_{Overall}$ score for the intersection can be averaged out to be 2.66. By referring to the *LOS* ranges mentioned in Table 4, the observed *LOS* category for the intersection is *LOS* E. Now, by inputting the values observed or taken from the field into the *MGGP* model (Eq. (7)), the predicted values of $ALOS_{Overall}$ scores can be calculated as: For first side of the approach, $ALOS_{Overall}$ score = 2.2 and for the other side of the approach, $ALOS_{Overall}$ score = 3.016. From the above calculations, it is evident that the predicted $ALOS_{Overall}$ scores for both the sides of the approaches are 2.2 and 3.016 respectively. Thus, the model predicts the scores with absolute errors 0.1 and 0.004 respectively. The predicted $ALOS_{Overall}$ score for the intersection can be averaged out to be 2.608. By referring to the *LOS* ranges mentioned in Table 4, the predicted *LOS* category for the intersection is also *LOS* E.

6.4 Ranges of ALOS classes (A-F)

An endeavour is made to check the application efficiency of the *LOS* scale defined above. All the through approaches of the signalised intersections considered in the study are assigned *ALOS* classes based on the classification mentioned in Table 4. Finally, the apparent and anticipated ALOS classes of each considered intersection are evaluated by averaging the apparent and anticipated estimations of $ALOS_{Overall}$ scores of all the approaches of the intersection and the outcomes are paralleled. It is found that out of 45 signalised intersections considered in the study, 42 have same perceived and predicted service classes. As perceived, the coordination amongst observed and anticipated *ALOS* classes is as high as 93.3%. Besides, the greatest deviation between the *ALOS* classes is just a single grade (viz., *LOS* C was anticipated rather than *LOS* D). It is in this way reasoned that the proposed *ALOS* model in combination with the *LOS* scale is efficient enough for field usage in the present setting.



(a) (b)

Fig. 5 Performance of MGGP based ALOS model showing the R^2 values for (a) training data (b) testing data

Table 4. Definitions and ranges of ALOS classes (A-F)

ALOS Class	Service Level	Ranges of $ALOS_{Overall}$ Scores
A	Excellent	>5.1
B	Very Good	>4.33- 5.1
C	Good	>3.5- 4.33
D	Average	>2.67- 3.5
E	Poor	>1.84- 2.67
F	Very Poor	<= 1.84

6.5 Roles and impacts of demonstrated factors in ALOS appraisal

It is a bit difficult to translate the impacts of the considerable number of factors just from the expressions of the formulated model since *MGGP* model is of somewhat complex nature. Along these lines, the general influences of individual characteristics are tried keeping in mind the end goal to guarantee their coherent accuracy. Sensitivity analysis is done to survey the relative significance of input factors in the formulated model. In this study, the sensitivity analysis is done with the help of the approach proposed by Gandomi. Two utilitarian qualities $f_{max}(v_i)$ and $f_{min}(v_i)$ are evaluated for each input variable (i = 1, 2,...n). The previous one speaks about the model yield when i^{th} variable has its most extreme perceived value, and remaining factors have their mean values. In the same way, the later one speaks about the model yield when the i^{th} variable has its minimum value, and remaining factors have their mean values. The most extreme deviation that a variable can make in the model yield (N_i) is assessed as: $N_i = f_{max}(v_i) - f_{min}(v_i)$. A positive estimation of N_i demonstrates that i^{th} variable has a positive influence $ALOS_{Overall}$ score. Whereas, a negative N_i speaks the reverse. According to the assumption of this work, a lower $ALOS_{Overall}$ score speaks regarding the most exceedingly awful service quality, and a higher $ALOS_{Overall}$ score speaks the opposite. Consequently, an input parameter having a positive influence on the $ALOS_{Overall}$ score has a positive impact on the administration quality and vive-versa. Table 5 demonstrates the N_i estimation of each input variable as achieved from the data analysis. It can be seen that v/w, control delay, queue length, N_v and E_n parameters have negative influences on the *ALOS* score, while *PCI* has positive influence on the same. In this way, *PCI* decidedly influences the *ALOS* class of road portions, while the others influence it contrarily.

The percentage involvement of each input variable (S_i) in the forecast of $ALOS_{Overall}$ score is assessed with the assistance of Eq. (8). This condition has been obtained from the ideas of Gandomi et al (2013). The S_i estimations of individual factors, as acquired, are condensed in Table 5. Thinking about the absolute estimations of S_i, positioning is offered to the variable having most astounding S_i value. Clearly, a higher S_i value assigns a greater impact of a variable. In this way, the factors are positioned in the same from rank-1 to rank-6 in view of the S_i values.

$$S_i = \frac{\operatorname{mod}(N_i)}{\sum_{i=1}^{n} \operatorname{mod}(N_i)} \times 100 \tag{8}$$

Table 5. Outcomes of Sensitivity Analysis.

Variables	*v/w*	*d*	*PCI*	Q_l	N_v	E_n
N_i	-4.9	-0.3	0.86	-0.4	-1.6	-0.2
S_i (%)	59.2	4.12	10.4	4.55	19	2.72
Rank	1	5	3	4	2	6

From the sensitivity analysis table, it can be inferred that v/w has the most noticeable impact on the prediction of $ALOS_{Overall}$ score since, it is the one to exert a highly significant influence on the $ALOS_{Overall}$ score. This factor has its contribution as high as 59.2% to the prediction of the model. Hence, it is ranked 'one'. It is observed to exert a remarkable impact on the operational qualities of automobiles. However, from the N_i value, it is evident that *v/w* has a negative influence on ALOS. After *v/w*, N_v is the second most influencing parameter in the prediction of $ALOS_{Overall}$ scores of signalised intersections. Its percentage contribution is as large as 19% in the development of *MGGP* model. From the N_i value, it is evident that the factor N_v has a negative influence on *ALOS* scores. It can be realised that with the increase in the percentage of non-motorised vehicles or the slow moving vehicles, there is an increase in hindrances to the fast moving mainstream vehicles. Pavement quality expressed on a five-point scale in terms of Pavement Condition Index also has a vital role to play in the prediction of $ALOS_{Overall}$ scores at signalised intersections. The better the pavement quality, the happier the users are, with the road. It is the third most affecting variable in the current study. Its percentage contribution is as high as 10.4% in the development of *MGGP* models. From the N_i value, it is evident that *PCI* has a positive influence on *ALOS* scores. The quality of vehicle operation is also determined by queue length and control delay. The longer the queue length, the greater is the delay experienced and the worse are the service facilities offered to the automobile users. From the point of view of prediction of satisfaction scores using *MGGP* technique, they are respectively the fourth and fifth most influencing parameters with their respective contributions as 4.55% and 4.12% to the model development. From the N_i values, it is evident that both of them exert negative influences on *ALOS*. Lastly, E_n is the least affecting variable and is ranked sixth in the model prediction. Its percentage contribution is as large as 2.72% in the development of *MGGP* model. From the N_i value, it is evident that the factor E_n has a negative influence on *ALOS* scores.

7. Conclusions

Since the number of automobile users is increasing at an alarming rate, this necessitates assessing the *LOS* of signalized intersections from the perspective of automobile users. The complexity of traffic movement in Indian scenario also demands that a study must be carried out for the fruitful planning and design of the signalised intersections. The following conclusions are obtained after conducting the study. All the input variables considered could not be directly used to develop the *ALOS* models. Hence, Pearson's Correlation Analysis was carried out to find out the significant variables out of all the input variables. Out of the 21 variables considered for the study, only six variables came out to be highly significant with their *p*-values less than 0.001. Volume per road width (*v/w*), control delay (*d*), pavement condition index (*PCI*), queue length (Q_l), effect of non-motorised vehicles (N_v) and obstructions due to encounters (E_n) were the six variables which came out to be significant as the outcomes of the significance test for *ALOS* model. Inter correlations among the variables were less than 0.8 which indicated that there was no chance of multi-collinearity. For the *MGGP* based *ALOS* model, the training data showed up the R^2 value as 0.975 while the R^2 value for the testing data was 0.875. Using *MGGP* based *ALOS* model for *ALOS* score prediction and hence, the service class, the percentage matching between the perceived and predicted *ALOS* categories was as high as 93.3%. Hence, this model could be effectively used for *ALOS* forecast at signalized intersections. From the model expression it could be deciphered that *ALOS* score increased with an increase in the value of pavement condition index and decreased with increase in volume per effective road width, control delay, queue length, effect of non-motorised vehicles and obstructions due to encounters. *v/w*, N_v and *PCI* were the highly influencing parameters affecting *ALOS* scores for the *MGGP* based delay model. Hence, it can be said that the results of this examination will to a great extent help the transportation planners and architects in making competent judgements for applying any changes to the existing signalised intersections thereby, laying the foundation of superior transportation networks.

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