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Service level modelling of motorized three-wheelers at un-signalized intersections under heterogeneous traffic conditions

Abhijnan Maji [1], Subhada Nayak[2*], M. Panda[3], P. K. Bhuyan[4]

[1]*M. Tech Student, Department of Civil Engineering, NIT Rourkela*
[2] *Ph.D. Scholar, Department of Civil Engineering, NIT Rourkela*
[3]*Assistant Professor, Department of Civil Engineering, NIT Rourkela*

Abstract

In developing nations like India, due to non-homogeneity in traffic streams, the flow of motorized three-wheelers gets clogged. While studying the literature, researchers do not find any significant Level of Service (LOS) models for forecasting motorized three-wheelers' service quality at uncontrolled un-signalized intersections under heterogeneous traffic conditions. This study brings to an AI-based Three-Wheeler Level of Service (3WhLOS) model to evaluate the service quality offered by un-signalized intersections operating under mixed traffic conditions. Data are collected from 21 uncontrolled intersections located at 7 different cities of India. Spearman's correlation analysis is performed to fathom the influence of service parameters towards perceived 3WhLOS score. Bayesian Regularized Artificial Neural Network (BRANN) is adopted for the prediction of 3WhLOS scores. Sensitivity Analysis is also executed to determine the relative importance of each parameter and help the transport authorities to identify the issues and improvise them for the betterment of the users.

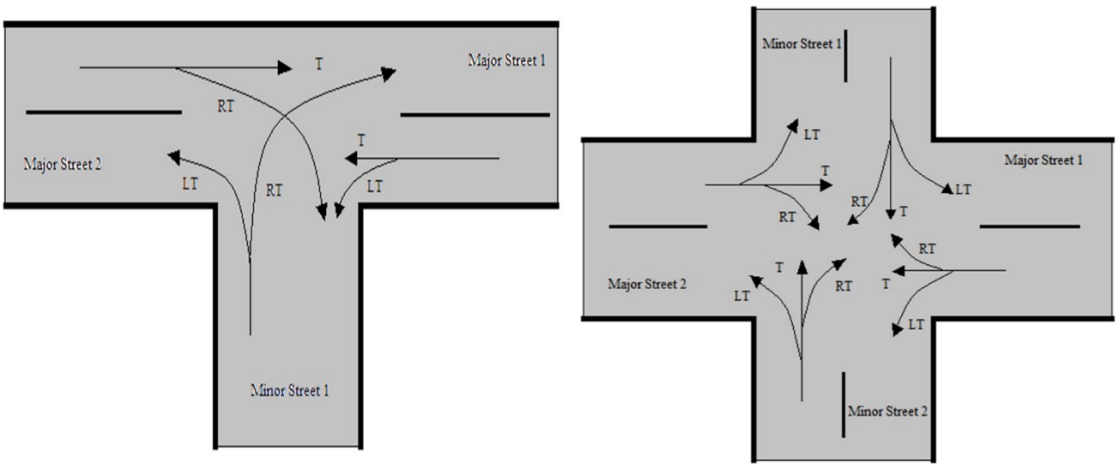
Keywords: Three-wheeler Level of Service (3WhLOS); Uncontrolled Un-signalized intersections; Heterogeneous Traffic; Artificial Intelligence (AI); Bayesian Regularized Artificial Neural Network (BRANN); Sensitivity Analysis;

1. Introduction

In this era of urbanization, an increasing number of people migrate to the urban and suburban parts of developing countries like India for better livelihood opportunities. As per 2011 census data given by the Government of India, the percentage of the urban Indian population has increased from 27.8 percent in 2001 to 31.16 percent in 2011. In India, the average traffic growth rate of three-wheelers per year is 7 to 8 percent. Due to the increased travel demand, an increasing number of vehicles run on the road, but the road infrastructures cannot be increased consistently. Hence, lack of space for vehicular traffic movement comes into the picture, resulting in traffic congestion. This research focuses on one of the crucial facilities of road network system, i.e., uncontrolled un-

* Subhada Nayak (subhadanayak@gmail.com)

signalized intersections. In un-signalized intersections, one stream of traffic flow from one approach looks for the gap in other streams of traffic flow from other approaches. A schematic diagram of three-legged and four-legged uncontrolled un-signalized intersection is given in Figure 1(a) and (b), respectively. In countries with relatively low per capita income levels, like India, it has been noticed that a considerable increase in the three-wheeler traffic on the road networks as one of the most pivotal para-transit modes in the urban, suburban as well as rural parts of the country. According to the data provided by the Ministry of Statistics and Programme Implementation, Government of India, as of March 2017, there are nearly 0.75 million registered three-wheelers running on Indian roads.



(a) (b)

Figure 1: Schematic diagram of (a) three-legged and (b) four-legged uncontrolled intersection

1.2 Problem Statement

In this era of superfast development, everybody wants to travel faster and expects a higher comfort level. Nobody wants to get stuck in a traffic jam and get delayed. Lane discipline is not followed in Indian roadways, resulting in a decrease in Level of Service (LOS). Maintaining the road facilities' service quality and the growing travel demand is now an immense challenge for transportation professionals. Many researchers have developed service prediction models for bicycles and automobiles by working on homogenous and heterogeneous traffic conditions. Limited research has been carried out to develop service prediction models for motorized three-wheelers plying under mixed traffic conditions. Most researchers have considered travel time and travel speed as the most influential parameters for developing LOS models. But this study proposes all those factors along with travel time and travel speed to be incorporated while model development.

2. Literature Review

An in-depth review of the literature is done to get well-acquainted with the previously performed research work that helps in identifying the shortcomings and ascertain the research gap. Auto-rickshaws account for three quarters of the world's fleet in India, these are three-wheeled motor vehicles generally hired in most developing countries to move both people and goods as stated by Mani and Pant (2011). These vehicles play an important role in urban transport in the country, being used for a wide

range of trip purposes and at considerably lower cost. Auto-rickshaws are more convenient, they are the only on hand mode of transportation offering door-to-door service along with on-demand service. Auto-rickshaw trips involve considerably lower walk when hired on the street and waiting times than do bus trips according to a study by. At off-peak times, the search for transportation easily ends up with finding Auto-rickshaws or Three-wheelers. They are also feasible away from public transit routes. Somehow making three-wheeler an important and convenient para-transit mode over cities those lack in public transit.

Brief numbers of researches have been done over homogenous traffic condition involving various aspects over a considerable number of impendent and how they affect the service quality of traffic modes and various facilities. In HCM-2000, service quality assessment has been explained taking on an eye to homogeneous traffic streams and factors affecting a non-heterogenous with appropriate lane discipline traffic streams has been taken into consideration. It defines LOS as a qualitative measure, representing the traffic stream's operating condition in terms of travel time, speed, control delay, volume to capacity (v/c) ratio, freedom to maneuver, traffic interruptions, comfort, and convenience. Prediction of such brief traffic stream service quality first different values are provided as boundaries to set a range of operating conditions for the six grades of LOS, i.e., "A" to "F". The quantitative measures of LOS cannot always represent the perceived service quality. The quantitative measures rather represent traffic flow characteristics. Flannery et al. (2005) concluded that the LOS methodologies present in HCM (2000) do not entirely represent drivers' perception[3]. HCM (2010) incorporated traveler's decision to rate the driving conditions on a scale of "very good" to "very poor" in the form of a questionnaire survey. Secondly, focusing on roadway facilities present and analysis of LOS at each road geometry is very much different considering various parameters of the concerned facility like an unsignalized intersection. Akcelik (2012) provided the influencing parameters that bothered the LOS and capacity of the un-signalized intersection and described the relationship between the various gap acceptance parameters and roadway geometry of un-signalized intersections[5]. Jamil *et al.* (2013) took into account four major traffic flow parameters, i.e. critical gap, follow-up-time gap, the proportion of heavy vehicles or motorcycles, and traffic volume for determining LOS[6]. HCM (2016) emphasized delay as the primary input parameter influencing the driver's satisfaction level at un-signalized intersections.

Various methods are introduced for quantifying the homogeneous traffic LOS. Major traffic flow parameters like volume, delay, capacity and critical gap etc. has been equated for LOS examination. Brilon (2008) introduced delay models based on the concept of queuing. Markov-chain technique has been used to validate the formulations of delay[8]. Chandra *et al.* (2009) developed a service delay model for heterogeneous traffic conditions and concluded that service delay is affected mainly by a higher percentage of heavy vehicles in the traffic stream[9]. Ashalatha and Chandra (2011) developed service delay models for passenger cars, two-wheelers, and heavy vehicles operating under heterogeneous traffic conditions[10]. Caliendo (2014) introduced a delay model for LOS prediction at an un-signalized intersection focussing on two input parameters, i.e., conflicting traffic volume and traffic volume entering intersections from minor roads[11]. Chodur *et al.* (2015) considered parameters like critical headways, headways between vehicles entering from a queue, vehicle speed, and drivers' behaviour to determine LOS at un-signalized intersections[12]. Zhang *et al.* (2017) introduced a conflict-based model utilizing Poisson regression[13].

Raff (1950) plotted a graph of cumulative probabilities of accepted and rejected gaps against available headway; their point of intersection gave the critical gap value[14]. Brilon *et al.* (1999) applied the Maximum Likelihood method to estimate the critical gap at the un-signalized intersections. Ning-Wu (2006) developed a methodology in which the probability distribution function of the accepted and rejected gaps and the critical gap is predicted by equilibrium probability between the two[15]. Mohan and Chandra (2018) considered the time of occupancy of a vehicle in the area of intersection as the vital attribute in deciding the critical gap[16].

3. Research Methodology

Based on the literature review, a four-step methodology is constructed for the present study to develop a reliable 3WhLOS model for un-signalized intersections operating with non-lane-based heterogeneous traffic. The steps are:

i. Selection of parameters having considerable influence ($p<0.001$) on perceived 3WhLOS score.
ii. Development of a BRANN-based 3WhLOS model for un-signalized intersections operating under heterogeneous traffic flow conditions.
iii. Fixing the ranges of associative 3WhLOS scores for six service categories (“A” to “F”).
iv. Determination of relative importance of the 3WhLOS model input parameters by applying sensitivity analysis.

Spearman’s correlation analysis is used when the inventory database has a number of categorical or ordinal input parameters. Hence, it is implemented to distinguish between the significant and the insignificant service parameters. The ‘p-value’ helps in selecting the more contributing parameters among many other service parameters. Generally, AI techniques like Artificial Neural Networks (ANN) are very productive and efficient in predictive modelling. Thus, a BRANN-based 3WhLOS model is developed to predict and assess the service quality offered by various uncontrolled intersections working under mixed traffic conditions from three-wheeler users’ point of view. Next, the ranges of the 3WhLOS scores associated with the six service classes are defined. Sensitivity analysis is carried out to understand the relative importance of the input variables used in the model.

In this study, the 3WhLOS scores are initially set to a six-point scale (i.e. 1 to 6), where 6 represent "excellent" driving condition, and 1 represents "very poor" driving condition. The mean of the scale is set as boundary between 3WhLOS grade 'C' and grade 'D'. The difference in 3WhLOS scores between 3.5 and 1 is 2.5, and the same is the difference between 6 and 3.5. Hence, to get the 3WhLOS scores of higher and lower classes, 2.5 is divided into 3 intervals, and 2.5/3, i.e. 0.833, is added to and subtracted from 3.5, respectively.

Table 1: Ranges of 3WhLOS scores for six service classes (A-F)

3WhLOS Category	*Level of Overall Satisfaction*	*Ranges of 3WhLOS scores*
A	Excellent	> 5.166
B	Very good	>4.333 – ≤5.166
C	Good	>3.5 – ≤4.333
D	Average	>2.667 – ≤3.5
E	Poor	>1.834 – ≤2.667
F	Very poor	≤ 1.834

4. Study Area and Data Collection

21 uncontrolled un-signalized intersections in 7 cities located in 5 different states of India are investigated for the purpose of the present study. The study has been conducted so that every possible variation in road geometries, traffic flow conditions, and built-environmental factors actually observed in Indian roadways are taken into consideration to possess an extensive database. The name of the cities and their respective locations across India from where the datasets have been collected are indicated in the map, as shown in Figure 2.

Rourkela, the 'Steel City' of Odisha, has a population of 536,450 and the highest per capita income in Odisha. A 16 km long Ring road links 19 sectors and some different parts of the city. Auto-rickshaws are the predominant para-transit option in this city. In Rourkela, the road networks mainly consist of un-signalized intersections and roundabouts.

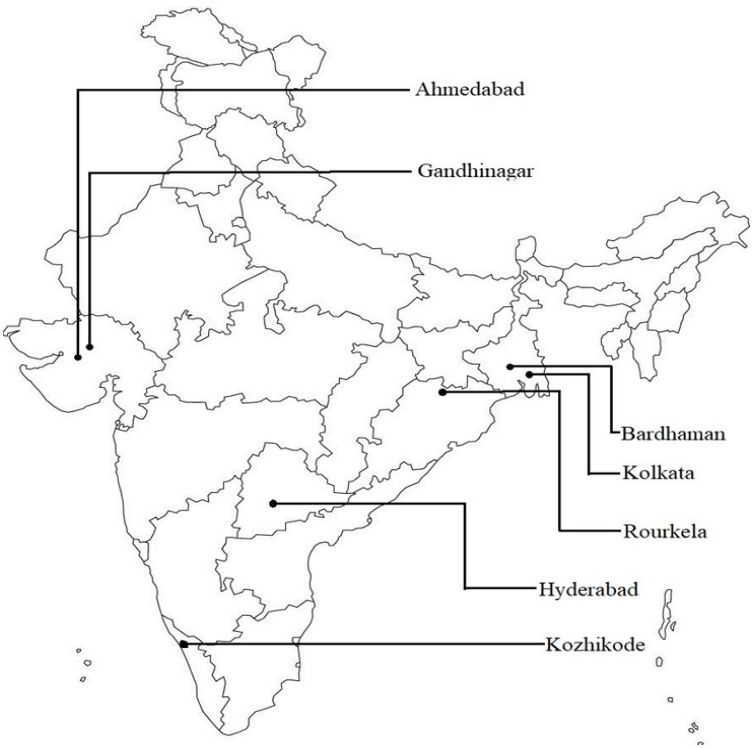
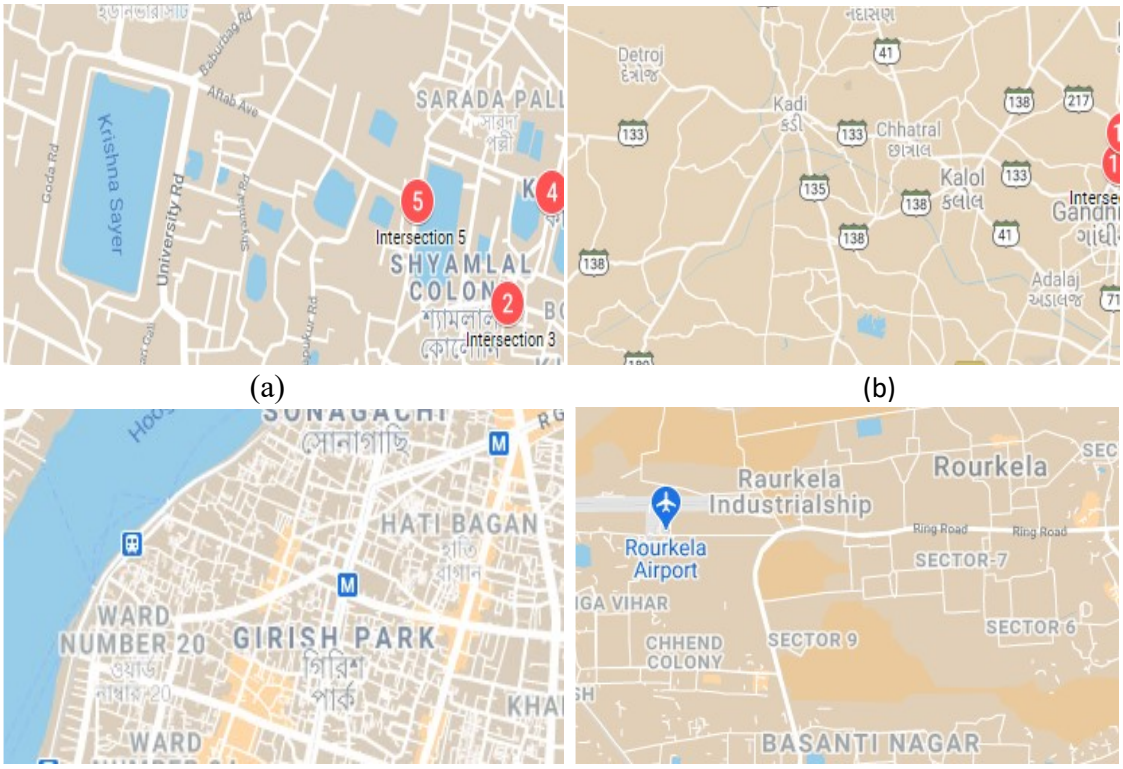


Figure 2: Location of the cities on the Indian map where the study has been conducted

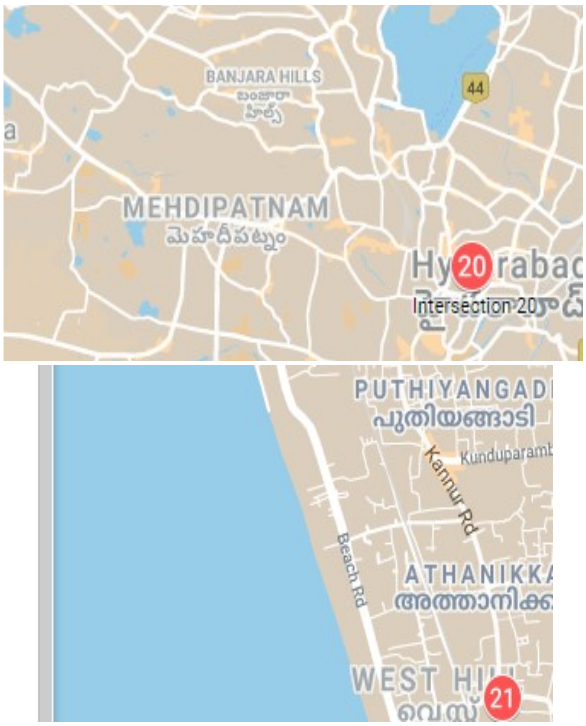
Bardhaman is one of the biggest cities in West Bengal in terms of area as well as population. It has an urban population of 347,016 with an average population density of 13,000/km^2. The city is intersected by the famous Grand Trunk Road (G.T.Road). NH-19 (previously NH-2) connecting Kolkata with Delhi bypasses the city. In this city, e-rickshaws (popularly called 'toto'), is one of the major para-transit modes. Kolkata, popularly known as the 'city of joy', has a population of 14.5 million with a metropolitan area is spread over 1,886.67 km^2. Since Kolkata is a very old city, the road networks are not adequately planned, even narrow and congested in many places. The two wings of the Golden Quadrilateral, i.e. Kolkata-Delhi and Kolkata-Chennai, start from this city. Ahmedabad, the former capital city of Gujarat, constitutes a metropolitan area of 1,866 km2 with an average population density of 11,000/km^2. Along with bus rapid transit system (BRTS), CNG powered auto-rickshaw is one of the principal modes of public transport. Gandhinagar is the present capital city of Gujarat, which constitutes an urban area of 326 km^2 with an urban population density of 900/km^2. Buses, minibuses, auto-rickshaws etc. are the major modes of public transports available in this city. Hyderabad, is the sixth most populous urban agglomeration in India with a metropolitan population of 68,09,970. As of 2012, more than 3.5 million vehicles are plying in this city, of which 3% are three-wheelers. NH-7, NH-65, NH-163 and NH-765 connects Hyderabad to various cities of India. Kozhikode, popularly known as Calicut, has a population of 550,440 and an urban area of 518 km^2 with an urban population density of 5200/km^2. The rate of literacy in Kozhikode city is 96.8%. NH-66, NH-766 and NH-966 connect Kozhikode to various cities of India.

The un-signalized intersections investigated in this study are indicated in the maps, as shown in Figure 3.



(a) (b)

(c) (d)



(e) (f)

Figure 3: Locations of un-signalized intersections across (a): Bardhaman city; (b): Ahmedabad and Gandhinagar; (c): Kolkata; and (d): Rourkela; (e): Hyderabad; (f): Kozhikode.

The data are collected during morning peak hour, i.e. 10:30 am to 11.30 am, and evening peak hour, i.e. 5 pm to 6 pm. The video clips are recorded on weekdays only. The video clips are played using VLC media player and IIT Bombay Traffic Data Extractor (TDE) software to extract the required datasets. A questionnaire is designed to collect the datasets regarding the qualitative variables such as the overall satisfaction (OS) score and seek the opinion of the three-wheeler users. The required geometric data can be obtained by simply vising the site of data collection. The traffic flow data were extracted from the videos recorded at various intersections. The vehicle's average speed (S_{avg}) at an un-signalized intersection is calculated by considering the time-mean speeds of 30 three-wheeler vehicles crossing each intersection. Service delay is calculated by taking the difference in time taken by a three-wheeler to cross the intersection in the presence and absence of any interfering traffic. The critical gap is extracted utilizing the equilibrium probability distribution method given by Ning-Wu (2012)[15]. Figure 4 gives the actual view of the critical gap observed in the field. On-street pedestrian volume can be obtained by counting the number of pedestrians manually from the video clips. The built-environmental parameters are extracted by examining the video clips at the un-signalized intersection, which are expected to affect the drivers' comfort level by creating an obstruction to the vehicular flow.

Figure 4: Actual view of the critical gap observed in the field

5. 3WhLOS Modelling Approaches

In this study, IBM SPSS version 24 has been utilized to perform all the modelling work. Before modelling, Spearman's Correlation Analysis is performed to check the degree of association among the continuous and discrete ordinal or categorical variables to produce a significant value. Spearman's Rho (ρ) value indicates the strength of the monotonic relation. After conducting correlation analysis, BRANN modelling tool (using MATLAB Simulink 2018b) is used for 3WhLOS model development.

5.1 Bayesian Regularized Neural Network (BRANN)

BRANN is a feed-forward multilayer perceptron (MLP) neural network that consists of one input layer, one output layer, and one or more hidden layer(s). Hidden layers use activation functions (AFs), such as tangent sigmoid, log-sigmoid and linear functions etc. to carry out suitable transformations. The back-propagation technique [17] is implemented in training the networks and estimating the weights and biases by reducing the sum squared error (SSE) of observed and predicted outputs.

The fundamental expression of a BRANN-based model with normalized output 'y_{BRANN}' within the range of [0–1] is as follow:

$$y_{BRANN} = f\left[b_0 + \sum_{k=1}^{h}\{w_k \times f(b_{hk} + \sum_{i=1}^{m} w_{ik}X_{ik})\}\right] \quad (1)$$

Where, f=transfer function, b_0=bias parameter at the output layer, w_k=weight between kth neuron of the hidden layer and the output neuron, b_{hk}=bias parameter at k^{th} neuron of the hidden layer, h=number of neurons in the hidden layer, w_{ik}=weight connected between i^{th} input variable and k^{th} neuron of the hidden layer, X_i=normalized value of ith input in the range [0–1].

6. Sensitivity Analysis

Sensitivity analysis of the input variables is carried out by implementing the equation given by Gandomi *et al.* (2013)[18], which is as follows:

$$S_i = \frac{\text{mod}\,[\,f_{max}(x_i) - f_{min}(x_i)\,]}{\sum_{i=1}^{n} \text{mod}\,[\,f_{max}(x_i) - f_{min}(x_i)\,]} \times 100 \quad (2)$$

Where S_i=sensitivity (%) of ith input, $f_{max}(x_i)$=Maximum value of predicted output over i^{th} input, $f_{min}(x_i)$=Minimum value of predicted output over i^{th} input, n=total number of input variables.

7. Results and Discussion

Spearman's correlation analysis has been performed to find out those independent variables that have a significant influence on the perceived 3WhLOS scores at uncontrolled un-signalized intersections.

Table 2: Spearman's correlation among input variables and perceived 3WhLOS

Variables	*Correlation with 3WhLOS*	*Significance*
On-street Parking Density (P)	-0.602	0.000
Pedestrian Volume (PedV)	-0.529	0.000
Average Speed (S_{avg})	0.814	0.000
Effective Lane Width (W_e)	0.431	0.000
Land Use Pattern (LU)	-0.370	0.000
Service Delay (T_s)	-0.614	0.000
Pavement Condition Index (PCI)	0.368	0.000
Presence of Median (PoM)	0.328	0.000
Obstruction due to Non-motorized vehicles (O_{NV})	-0.494	0.000

Correlation among input variables (ρ value)

Variables	P	PedV	S_{avg}	W_e	LU	T_s	PCI	PoM	O_{NV}
P	1.000	0.774	-0.753	-0.530	0.575	0.513	-0.420	-0.586	0.427
PedV	0.774	1.000	-0.591	-0.316	0.547	0.356	-0.358	-0.417	0.526
S_{avg}	-0.753	-0.591	1.000	0.601	-0.502	-0.528	0.522	0.480	-0.652
W_e	-0.530	-0.316	0.601	1.000	-0.224	-0.461	0.397	0.478	-0.416
LU	0.575	0.547	-0.502	-0.224	1.000	0.287	-0.069	-0.218	0.317
T_s	0.513	0.356	-0.528	-0.461	0.287	1.000	-0.215	-0.394	0.179
PCI	-0.420	-0.358	0.522	0.397	-0.069	-0.215	1.000	0.247	-0.443
PoM	-0.586	-0.417	0.480	0.478	-0.218	-0.394	0.247	1.000	-0.363
O_{NV}	0.427	0.526	-0.652	-0.416	0.317	0.179	-0.443	-0.363	1.000

Spearman's correlation analysis provides a total of nine significant input variables with two-tailed significance (p)< 0.001. Thus, these independent input variables are considered for the development of 3WhLOS model in the present study. On-street Parking Density(P) is measured as percentage of parked road length. Pedestrian Volume (PedV) is the number of pedestrians crossing the intersection (pedestrians per hour). Average Speed (S_{avg}) is the arithmetic mean of spot speed. Effective Lane Width (W_e) is

the lateral width available excluding roadside or on street commercial activities and parking, for smooth movement of traffic. Land Use Pattern (LU) is observed as three categories; residential area, mixed land use area and Commercial are. Service Delay (Ts) is the time spent waiting for an opportunity to enter an intersection. Pavement Condition Index (PCI) is obtained using a five-point scale (1: worst to 5: excellent). Presence of Median (PoM) is noted with field observations. Obstruction due to non-motorized vehicles (O_{NV}) expressed as a percentage of non-motorised traffic volume to the total traffic volume. The complete database consists of 110 approaches of 21 uncontrolled un-signalized intersections, out of which 70 percent data are used for the model development process, and the remnant 30 per cent are utilized to validate the model.

7.1 BRANN modelling approach:

All the predictor and output variables are normalized in the range of [0,1]. A number of BRANN models with different numbers of hidden neurons ranging from 1 to 15 are constructed. The prediction results of five superior performing models are presented in Table 3. BRANN model-4 with eleven hidden neurons and tan-sigmoid transfer function has produced the best results.

Table 3: Best outcomes of different BRANN models

model no	*1*	*2*	*3*	*4*	*5*
no. of hidden neuron	4	7	10	11	12
transfer function	log-sig	log-sig	tan-sig	tan-sig	log-sig
Optimum performance in the training phase					
R^2	0.92103	0.8952	0.91979	0.94254	0.91596
AAE	0.0374	0.0034	0.05581	0.02016	0.00181
RMSE	0.29141	0.3407	0.30208	0.2572	0.312903
Optimum performance in the testing phase					
R^2	0.85838	0.85815	0.89439	0.89923	0.85686
AAE	0.09299	0.02519	0.09589	0.06475	0.05099
RMSE	0.39748	0.39613	0.35024	0.32724	0.40838
Model generalization ability					
Overfitting Ratio (OR)	1.3639889	1.162694	1.159428	1.272317	1.305133

Table 4: Weights and Biases of BRNN model-4

Hidden	*Weights*									*Biases*		
Neurons	W_e	*PCI*	*PoM*	*LU*	*P*	O_{NV}	*PedV*	T_S	S_{avg}	w_k	b_{hk}	b_0
1	-0.003	0.002	-0.064	0.071	0.033	0.052	-0.135	-0.011	0.050	0.172	0.008	0.037
2	0.115	0.157	0.386	-0.132	-0.163	-0.327	0.094	0.047	0.422	0.172	-0.236	
3	0.003	0.002	-0.064	0.071	0.033	0.052	-0.135	-0.011	-0.050	0.172	0.008	
4	0.003	-0.002	0.064	-0.071	-0.033	-0.052	-0.135	0.011	0.050	-1.344	-0.008	
5	-0.903	0.626	0.174	-0.307	-1.102	-0.286	-0.279	-0.404	-0.415	1.313	-0.126	
6	0.266	0.805	0.306	-0.356	-0.229	-0.666	0.079	-0.354	0.825	1.053	-0.271	
7	0.890	0.132	0.107	-0.690	-0.288	-0.460	-0.789	-0.593	0.109	0.172	-0.445	
8	-0.016	0.568	0.115	-0.381	-0.730	-0.593	-0.077	-0.259	-0.660	-1.238	0.004	
9	0.007	-0.009	-0.544	-0.225	-0.175	-0.787	-0.676	-0.424	0.557	-0.172	0.286	
10	0.003	-0.002	0.064	-0.071	-0.033	0.052	-0.135	0.011	0.050	-0.731	-0.008	
11	-0.003	0.002	-0.064	0.071	0.033	0.052	0.135	0.011	-0.050	-0.172	0.008	

The mathematical form to predict the 3WhLOS using BRNN model can be expressed as:

$$A_1=0.008-0.003\times W_e+0.002\times PCI-0.064\times PoM+0.071\times LU+0.033\times P+0.052\times O_{NV}+0.135\times PedV-0.011\times T_S-0.05\times S_{avg} \quad (3)$$

$$A_2=-0.236+0.115\times W_e+0.157\times PCI-0.386\times PoC+0.132\times LU-0.163\times P+0.327\times O_{NV}+0.094\times PedV+0.047\times T_S-0.422\times S_{avg} \quad (4)$$

…

$$A_{11}=0.008-0.003\times W_e+0.002\times PCI-0.064\times PoC+0.071\times LU+0.033\times P+0.052\times O_{NV}+0.135\times PedV+0.011\times T_S-0.05\times S_{avg} \quad (5)$$

Similarly, $B_1=0.172\times A_1$ (6)

…

$B_{10}=-0.731\times A_{10}$ (7)

$B_{11}=0.172\times A_{11}$ (8)

$3WhLOS_N=0.037+B_1+B_2+\ldots+B_{11}$ (9)

Where, A_1, A_2,..,A_{11} and B_1, B_2,..,B_{11} are the general terms of the BRANN model.

Finally, $3WhLOS_N$ (normalized 3WhLOS score) is de-normalized to get the predicted 3WhLOS score for respective approaches of un-signalized intersections. The proposed BRANN model shows good R^2 values of 0.9425 and 0.8992 for both training and testing datasets, respectively.

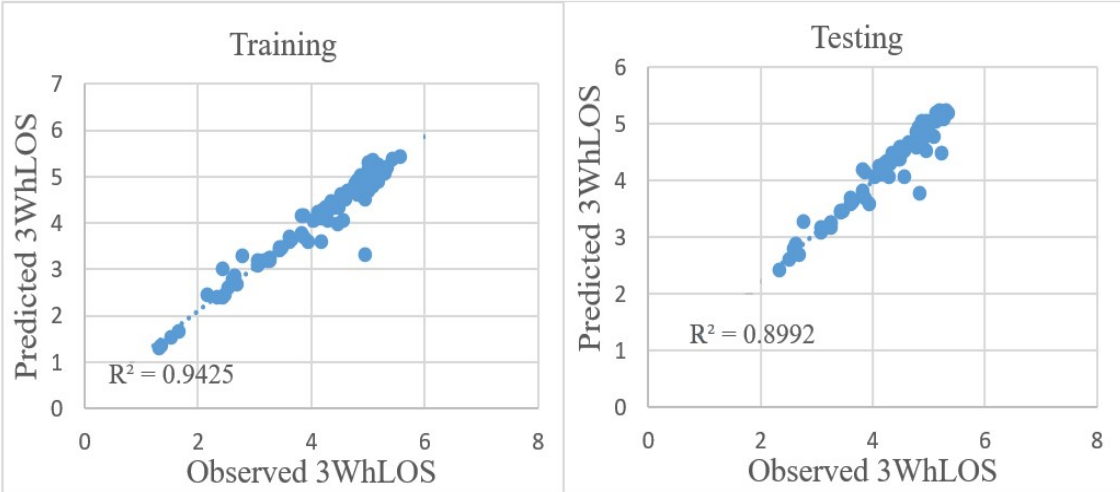


Figure 6: Validation plots of BRANN model

The BRANN model is then utilized to predict the 3WhLOS scores offered by different intersections considered in the database. It is found that around 4.54%, 33.64%, 35.45%, 14.54%, 8.18%, and 3.65% of the uncontrolled intersections are providing service categories of 'A', 'B', 'C', 'D' 'E' and 'F' respectively for three-wheeler mode of transport.

7.2 Model application

An example is provided to understand the implementation of the proposed 3WhLOS model in the field. The followings are the observations collected from 'Kalna Road, Bardhaman'. The steps to calculate 3WhLOS for this intersection are:

For Major road 1 (Right Turning): W_e=6.2, PCI=5, PoM=1, LU=0.15, P=0.13, O_{NV}=0.14, PedV=95, T_S=1.68 and S_{avg}=2.04. The predicted value of 3WhLOS is calculated as 3.29 (using equation 3 to 9) with 3WhLOS category 'C'.

Similarly, for Major road 1 (Through): W_e=6.2, PCI=5, PoM=1, LU=0.15, P=0.13, O_{NV}=0.14, PedV=118, T_S=1.36 and S_{avg}=2.78. The predicted 3WhLOS is calculated as 4.71 with 3WhLOS category ‘B’.

For Minor road (Right Turning): W_e=4.6, PCI=5, PoM=0, LU=0.15, P=0.13, O_{NV}=0.14, PedV=98, T_S=2.51 and S_{avg}=1.9. The predicted 3WhLOS is calculated as 3.39 with 3WhLOS category ‘C’.

For Major road 2 (Through): W_e=6.2, PCI=5, PoM= 1, LU=0.15, P=0.13, O_{NV}=0.14, PedV=112, T_S=1.23 and S_{avg}=2.51. The predicted 3WhLOS is calculated as 4.40 with 3WhLOS category ‘B’.

Hence, the overall 3WhLOS score for the intersection is 3.95. The perceived 3WhLOSoverall score for the intersection can be averaged out to be 3.98. By referring to Table 1, the predicted 3WhLOS category for the intersection is designated as 3WhLOS category 'C'.

7.3 Sensitivity Analysis

The sensitivity values (S_i %) obtained for each variable of the un-signalized intersection 3WhLOS model are presented and ranked in Table 5.

Table 5: Sensitivity analysis of 3WhLOS model attributes

Variable	W_e	PCI	PoM	LU	PedV	O_{NV}	T_S	S_{avg}	P
Si (%)	3.6	6.16	3.55	7.75	11.32	9.43	29.42	18.6	10.17
Rank	8	7	9	6	3	5	1	2	4

Few improvement strategies which can be implemented to reduce the issues related to the movement of three-wheelers at un-signalized intersections are:

a) Service delay (T_s) can be reduced by separating the movements of heavy vehicles, slow-moving non-motorized traffic and pedestrians which are having major contribution towards the calculation of average speed (S_{avg}), the second highly proportional parameter in regard of 3WhLOS patterns (where separate foot-path is unavailable) from the flow of three-wheelers.
b) Average speed can be increased by reducing the factors that cause hindrance in the flow, such as poor pavement condition; as PCI with S_{avg} having a correlation of -0.522, heavy vehicles movement that affects service delay (Ts); the major contributing parameter to examine 3WhLOS with 29.42%, slow moving non-motorized traffic; as O_{NV} is inversely proportionating with S_{avg} by -0.652, pedestrians; as PedV correlates with S_{avg} by -0.528, etc.
c) Grade separated foot-paths can be constructed to reduce the pedestrian movement along the sides of the roadways.
d) Off-street parking lots need to be constructed, and stringent regulations need to be imposed to prevent on-street parking.
e) Illegal movement of slow-moving non-motorized vehicles should be restricted by imposing strict regulations to enhance driver's satisfaction at uncontrolled intersections.
f) On-street vending activities should be minimized to enhance the service quality of respective intersections.
g) Pavement surface requires regular maintenance for a smooth ride of vehicles.
h) Roadside encroachment ought to be restricted so that the road's effective width remains wide enough for the easy movement of three-wheelers.
i) Through traffic should be separated from altering traffic with the help of a median barrier to increase drivers' comfort and safety at un-signalized intersections.

8. Conclusion

After carrying out a thorough inspection and modelling of un-signalized intersections' service quality from three-wheeler users' perspective, different conclusions can be drawn. The mixed traffic conditions in India make traffic operation and its management very much tricky. That is why the database has been prepared by collecting datasets from different parts of the country. W_e, S_{avg}, PCI, P, LU, T_S, O_{NV}, PoM and PedV comes out to be the most significant variables affecting 3WhLOS scores with two-tailed significance (p)< 0.001. BRANN model comes up with a satisfying 3WhLOS score prediction efficiency. BRANN model is then implemented to predict the 3WhLOS scores, and it is observed that maximum number of intersections are offering 3WhLOS category 'C'. From the sensitivity analysis, it is observed that service delay has the highest negative impact of 29.42% and average speed has the highest positive impact of 18.6%. Hence, if the service delay can be reduced, and the three-wheelers'

average running speed can be increased as T_s is inversely affected by S_{avg} with a correlation value of -0.528, the service quality offered by the intersections can be ameliorated. The sensitivity analysis carried out in this study will help the transportation professionals to understand the operational barriers and to develop road facilities with a superior driving condition by keeping an eye on major variables like Lane width(We), Land use pattern (S_i of LU is 3.6%), Pavement condition(S_i of PCI is 6.16%), Presence of median(S_i of POM is 3.55%), etc. The model developed in this study can also be implemented in the developed countries having homogeneous traffic flow conditions only after performing certain alterations in the input variables depending upon the road geometry, traffic flow and built-environmental conditions.

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