

MODELLING SATURATION FLOW AT SIGNALIZED INTERSECTIONS IN MIXED TRAFFIC CONDITIONS: ARTIFICIAL NEURAL NETWORK APPROACH

Sushmitha Ramireddy* and Ravishankar KVR

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Abstract

Saturation flow rate is very important parameter which was used extensively in the design and control of signalized intersections. In the present study saturation flow is estimated with cycle time, approach width, proportion of two wheelers, proportion of three wheelers and proportion of cars using regression analysis and Artificial Neural Networks. A comparison of MLR and ANN prediction of field saturation flow is made, and the study results showed that ANN are highly accurate because of their self-computing and intelligent behaviour. Mean absolute percentage error (MAPE) value is less and Index of Agreement (IA) value is high for best fitted ANN model when compared to those for MLR and INDO HCM models. The developed ANN satisfactorily predicted the saturation flow at signalized intersections in mixed traffic conditions with MAPE of 1.76% and with IA of 0.999.

Keywords: Mixed traffic, traffic composition, Artificial Neural Network, Indian highway capacity manual

Introduction

In urban road network signalized intersections plays a vital role. The efficient operation of the signalized intersection yields efficient road network operation. The capacity of signalized intersections depends on saturation flow rate

and control delay. Accurate estimation of saturation flow is very important for the efficient design of signalized intersections, which in turn operates the whole network efficiently. Saturation flow occur, when there

Department of Civil Engineering, National Institute of Technology Warangal, India-506004, E-mail: susmitharamireddy@gmail.com, kvrrshankar@gmail.com

* Corresponding author

is a continuous movement of vehicular traffic even if the 100% green time is given. Studies around the world proposed various models for the estimation of saturation flow for a given green time. But, most of the studies are based on western traffic conditions and vehicular traffic strictly follows lane discipline. The traffic condition in developing countries like India is mixed type with poor or no lane discipline. In the present study, an attempt is made to develop signalized intersection saturation flow model to cater for the non-lane based mixed traffic flow conditions.

Artificial Neural Networks have been used in various fields of research such as Engineering, Medical, Agricultural etc. Artificial Neural Networks were introduced by Warren McCulloch and Walter Pitts in 1943. Zhao and Thorpe (2000) developed pedestrian flow prediction model using ANN. Murat and Baskan (2006) developed a model for estimating control delay for vehicular traffic using ANN. Dogan *et al.* (2016) estimated delay and number of stops per vehicle using ANN approach. Preethi *et al.* (2016) presented a modified Webster's delay formula for heterogeneous traffic conditions by proposing a field adjustment term using ANN approach. Yugendar and Ravishankar (2018) analysed crowd flow parameters using Artificial Neural Networks. Thus, the predictability of ANN is better in comparison to other models and has widespread applications.

Many researchers in the earlier studies had tried to model saturation flow rate with factors: approach width, proportion of two wheelers, proportion of heavy vehicles, etc. by using MLR models, however, these models included limited parameters in the saturation flow models (Potts *et al.* 2007, Budi and Solihin, 2011, Anusha *et al.*, 2013, Shrestha and Anil, 2014). Results from linear regression models are easy to interpret but they have limitations in their assumptions such as equal variance, independence, multicollinearity and normality. In addition, the MLR models shows low R^2 value and poor correlation between independent and dependent variables, compared to non-linear models (Abyaneh, 2014). There are several influencing factors (Geometric,

traffic and control characteristics) that has a considerable impact on the saturation flow under mixed traffic conditions. Hence, ignoring such influencing variables, because of statistical significance is inconsistent. And it is not always possible to fit a linear relationship between variables because in the real scenario the variables may have a non-linear relationship. Fitting a linear model in such cases may lead to over estimation or under estimation of the values. Traffic in developed countries and in India are entirely different not only in vehicular composition but also in driver behavior where there is a frequent lane change. In such scenario linear models may not yield the accurate results. Such a limitation of MLR models can be overcome by non-linear (ANN) models, which considers the impact of various variables on saturation flow under mixed traffic conditions. In this paper an attempt is made to estimate the saturation flow values using both the models to suggest the best model for heterogeneous traffic conditions based on the prediction capabilities.

MLR and ANN models are proposed in the present study considering the effect of cycle time, approach width, proportion of two wheelers, proportion of three wheelers and proportion of cars on saturation flow. The aim of the present study is to model and compare the prediction capabilities of MLR and ANN models in estimating the saturation flow at under mixed traffic conditions.

Literature Review

Scientists around the world, who carried out their research in this area, developed various models for the estimation of saturation flow rate. But most of them are based on homogeneous traffic conditions. Saturation flow is defined as the steady state discharge rate of queued vehicles from an approach at a signalized intersection with continuous green and an infinite queue (INDO HCM 2017). In practice, it is measured as the maximum departure rate of queued vehicles from an approach during the green interval measured at the stop line under prevailing conditions. It is

measured in pcu/h of green. Once the green interval commences, the flow will be less as vehicles need to accelerate from their stop. The flow will increase gradually, after some period and reaches a steady state maximum flow condition. This condition is referred to as saturation flow condition. But when amber period starts, the flow will start decreasing to a minimum value and attains zero (Turner and Harahap, 1993). Saturation flow rate of signalized intersection depends on various factors like green time, cycle time, width of approach, peak hour volume, traffic composition and proportion of turning traffic.

Arasan and Vedagiri (2006) studied the effect of width of roadway on saturation flow under heterogeneous traffic using HETEROSIM simulation package. The results show that, with the increase in width of approach, the saturation flow increases significantly. Potts *et al.* (2007) conducted a study on saturation flow considering the effect of lane width. Results indicated that the saturation flow varies significantly with lane width. For 2.9 m lane width the saturation flow was found to be 1,736 to 1,752 pc/h/ln, for 3.3 to 3.6 m lane width the saturation flow was found to be 1,815 to 1,830 pc/h/ln and for widths greater than 4m the saturation flow was found to be 1,898 to 1,913 pc/h/ln. The saturation flow rates measured are less than those estimated by HCM 2010. Budi and Solihin (2011) estimated saturation flow using $S = 600 W_e$, which is commonly used in Indonesia. When the width of approach is ranging between 3 m to 8.9 m, then the field values are closer to those obtained from the formula and for road widths varying between 9 m to 12 m, there was a considerable difference between field and calculated saturation flow rate values. For larger road widths the proposed saturation flow relation is $S = 500 W_e + 400$. Anusha *et al.*, (2013) observed a significant correlation between saturation flow and proportion of two wheelers with a correlation coefficient of 0.42 to 0.94. Results show that the capacity varies directly with the volume of two wheelers and inversely with the volume of all other vehicle categories.

Shrestha and Anil (2014) developed linear regression models for estimating Passenger car units and saturation flow. Various parameters like width of approach, green time, percentage right turning vehicles, percentage heavy vehicles, percentage two wheelers and parking are considered for developing regression models. The developed model shows good correlation with field data. Nguyen (2016) developed a saturation flow model converting all vehicle classes into motorcycle unit. It was found that the motorcycle saturation flow in road width of 3.5 m could reach to 11,300 mcu/h, which was 5.8 times higher than the saturation flow of lane disciplined and homogeneous traffic situation (1,900 pcu/h). Chand *et al.* (2016) conducted a study on saturation flow at selected intersections in Delhi. Dynamic PCU method was adopted to convert the traffic from heterogeneous condition to homogeneous condition. Three separate saturation flow models are developed by considering three different factors such as approach width, percentage of cars and percentage of two wheelers one at a time. Gowri *et al.* (2016) determined PCU values for three different vehicle categories using a microscopic simulation model using headway ratio method. Also, the influence of traffic volume, percentage of different categories of vehicles and width of the road on saturation flow was found. A regression equation was developed to estimate passenger car equivalents. Saha *et al.* (2017) presented a linear model for estimating saturation flow considering the factors like road width, traffic composition and percentage of right turning vehicles. For the purpose of field measurement of saturation flow, arrival rates as well as departure rates of vehicles were collected at five second count intervals. The developed saturation flow model estimates saturation flow of study intersections with a maximum error of 9.5%. Preethi and Ashalatha (2018) estimated saturation flow based on area occupancy concept. A regression equation was developed for estimating saturation flow considering width of approach and traffic

composition. VISSIM software tool was used to produce saturation flow data for varying approach width and traffic compositions. The results indicated that as heavy vehicles increase there is a decrease in saturation flow.

Researchers around the globe developed regression equations for estimating saturation flow. It is observed and understood that, the multiple linear regression models are either over-estimating or under-estimating the saturation flow. Models developed in the previous studies, for estimating saturation flow along with its error are presented in Table 1. In order to minimize the errors and maximize the accuracy in estimating saturation flow, in the present study, an attempt is made, to estimate saturation flow using ANN and its validity in applying to mixed traffic flow condition. In this analysis, the saturation flow is modelled using multiple linear regression and is compared with the ANN.

Data

For the present study, six intersections are selected. Malaparamba intersection, Thodayad intersection and Eranhipalam intersections are in Calicut city, Kakatiya University (KU) intersection and Kazipet railway station intersections are in Warangal city and Suchitra intersection is in Hyderabad city, India. Video recording is done to collect traffic data from the field. Video recording is done by placing the camera on the top of the adjacent building so that the stop lines of all the four legs of the intersections are clearly visible. Roadway data approach width, number of lanes is collected manually from the site. The geometric and control details of the intersections are presented in Table 2.

The approach widths of the selected intersections are varying from a minimum

Table1. Multiple linear regression equations developed in the previous studies

Author	Equation	Accuracy and (or) Error measurements
Preethi and Ashalatha (2018)	$S = 550 + 101nW + 3P_{2w} - 2.5P_b - 2P_{3w}$	MAPE = 8.4%
Saha <i>et al.</i> (2017)	$S_{total} = 1,395 + 35 \times P_{tw} - 63 \times P_{hv} + 34 \times P_{RT}$	Percentage error 8-10%
Susilo and Solihin (2011)	$S = 500 \times W_e + 400$	Percentage error -6% to + 11.78%
Hossain (2001)	$Q_s = 1,500 + 430 \times W_d + 10.5 \times P_{nmv} - 30 \times P_{hv}$	Error 270

Table 2. Geometric and control details of the selected intersections

Intersection	Approach name	Approach width (m)	Cycle time (sec)	Green time (sec)	Amber time (sec)
Eranhipalam	Kannur	7.9	180	46	3
	REC	7.9		44	3
	Calicut	7.1		38	3
	Ariyadthupalam	10.9		40	3
Kazipet Railway Station	Hyderabad	8.8	130	35	5
	Vishnupuri	6.0		15	5
	Hanmakonda	10.2		35	5
	Kazipet Railway station	7.7		25	5
Malaparamba	Kannur	7.2	180	30	3
	REC	7.5		60	3
	Thodayad	7.0		33	3
	Calicut	5.6		45	3
Kakatiya University Cross roads	100 feet road	7.0	150	27	3
	Public gardens	7.5		42	3
	University bypass	9.0		27	3
	Karimnagar	7.0		42	3
Suchitra	Old alwal	10.5	200	18	2
	Bowenpally	10.0		78	2
	Suchitra road	7.5		28	2
	Bashirabad	10.0		68	2
Thodayad	Malaparamba	6.0	180	38	3
	Trissur	7.5		32	3
	REC	7.5		40	3
	Calicut	7.9		58	3

width of 5.6 m for Calicut approach of Thondayad intersection to a maximum width of 10.9 m for Ariyadthupalam approach of Eranhipalam intersection. The minimum green period is observed as 15 sec for Vishnupuri approach of Kazipet railway station intersection and the maximum green period is observed as 78 sec for Bowenpally approach of Suchitra Intersection. From the playback videos, volume count and turning proportions are extracted for every 5 min count interval. The peak hour traffic volume proportions and turning proportions of the selected intersections are presented in Table 3. From Table 3 it is very clear that the proportion of two wheelers and cars is very high, and the proportion of non-motorized vehicle is very low and is neglected.

Saturation Flow Estimation

In the present research work, stop line is taken as reference line and the number of vehicles passing through the reference line is considered for every 5 sec count interval during green intervals. Saturation flow is estimated by taking classified vehicle volume count for each successive 5 sec count interval

during saturated green period. The intervals are considered up to at least there are two vehicles passed through the reference line. The saturation flow is estimated as shown in Equation 1 (INDO HCM, 2017). The estimated saturation flow is converted in pcu/h using pcu values suggested by INDO HCM (2017) for mixed traffic conditions and are given in Table 4.

$$S = \sum p_i n_i \times \frac{3600}{CI} \quad (1)$$

where,

S = Saturation flow in pcu/h crossing the stop line,

p_i = passenger car unit of vehicle type i ,

n_i = number of vehicles of type i crossing the stop line during the count interval (CI),

CI = count interval (in seconds).

The INDO HCM pcu values used in the present study are valid when proportion of heavy commercial vehicles/bus is not more than 15% of total traffic volume emerging from an intersection approach. In the present study the proportion of heavy vehicles/bus is less than 15%.

Table 3. Peak hour traffic volume proportions and turning movements

Intersection	TW	3W	Cars	LCV	HV	NMV	through	right	left
Malaparamba	0.4	0.05	0.4	0.06	0.01	0.008	0.51	0.18	0.29
University cross roads	0.3	0.18	0.2	0.14	0.03	0.008	0.53	0.22	0.23
Thondayad	0.4	0.03	0.4	0.02	0.02	0.001	0.61	0.16	0.21
Eranhipalam	0.4	0.10	0.3	0.09	0.03	0.008	0.43	0.24	0.32
Suchitra	0.5	0.03	0.3	0.00	0.00	0	0.51	0.17	0.31
Kazipet railway station	0.3	0.25	0.1	0.15	0.05	0.002	0.45	0.26	0.27

Table 4. INDO HCM pcu values

Vehicle type	Passenger car unit
Motorized traffic	
Two wheelers (tw)	0.4
Auto Rickshaws (Auto)	0.5
Car	1.0
LCV	1.1
HCV	1.6
Bus	1.6
Non-Motorized traffic	
Bicycle	0.3
Cycle rickshaw	1.8
Hand/ animal drawn cart	4.0

Saturation Flow Estimation using Regression Analysis INDO HCM

Recently, INDO HCM has developed with an objective to illustrate nationwide characteristics of traffic and determine the capacity and LOS for mixed traffic for various urban and interurban roads with consideration of various highway facilities like mid blocks, un signalized intersections, signalized intersections and roundabouts. In INDO HCM, base saturation flow rate is correlated with geometric and traffic characteristics. The base saturation flow is calculated using Equation 2 and saturation flow rate is calculated using Equation 3.

$$USF_0 = \begin{cases} 630 & \text{for } w < 7m \\ 1140 - 60w & \text{for } 7 \leq w \leq 10.5m \\ 500 & \text{for } w > 10.5m \end{cases} \quad (2)$$

where,

USF_0 = base saturation flow rate (pcu/h/m),

w = width of approach (m).

The prevailing saturation flow rate of the intersection approach for the movement group under consideration is then obtained as presented in Equation 3 (INDO HCM, 2017).

$$SF = USF_0 \times W \times f_{bb} \times f_{br} \times f_{is} \quad (3)$$

where,

SF = Saturation flow rate in pcu/h,

W = width of approach in m,

USF_0 = base saturation flow rate,

f_{bb} = bus blockage adjustment factor due to the presence of bus stop on curb side,

f_{br} = adjustment factor for right turning vehicles due to the presence of through vehicles,

f_{is} = initial surge adjustment factor.

In the present study, cycle time, peak hour volume, approach width, vehicle composition and proportion of turning vehicles are considered. Significant correlation of saturation flow is observed with cycle time, Approach width, proportion of two wheelers, three wheelers and proportion of cars. The correlation coefficients obtained for significant variables are presented in Table 5. The positive sign associated with the cycle time in the correlation matrix indicates that, the saturation flow increases with the increase in cycle time. Also, the saturation flow increases with the increase in approach width, percentage of two wheelers and percentage of cars. As the acceleration capabilities of these two kinds of vehicles are high, they clear the intersection in a faster manner. Therefore, the saturation flow increases. On another hand the saturation flow decreases with the increase in the proportion of three wheelers. The acceleration capability of three wheelers is less compare to two wheeler and car and they clear the intersection slowly, which results into the reduction of saturation flow. The Equation 4 represents the model form obtained for the estimation of saturation flow.

$$S = 5.8C + 166w + 55p_{tw} - 10.4p_{3w} + 11.14p_c - 1464 \quad (4)$$

where,

S = saturation flow in pcu/h,

C = cycle time in seconds,

W = approach width in meters,

P_{tw} = proportion of two wheelers,

P_{3w} = proportion of three wheelers,

p_c = proportion of cars.

Table 5. Correlation matrix showing significant variables

	S	C	W	P _{tw}	P _{3w}	P _c
S	1					
C	0.71	1				
W	0.46	0.27	1			
P _{tw}	0.77	0.24	0.36	1		
P _{3w}	-0.62	-0.22	-0.116	-0.16	1	
P _c	0.56	0.34	0.104	0.31	-0.32	1

The R^2 value obtained for the model is 0.72. From the model, it is observed that the saturation flow value increases with increase in cycle time, Approach width, proportion of two wheelers and cars and it decreases with the increased proportion of three wheelers. The R^2 value obtained from the empirical model/linear regression model is not satisfactory. For better R^2 value and Index of Agreement (IA) and lower Mean absolute percentage error, artificial neural networks have been experimented in the present study.

Artificial Neural Network (ANN) Modelling

In the present study, ANN approach is adopted for predicting saturation flow rate. The modelling technique adopted in the present study is a multilayer feed forward ANN. The neural networks consist of number of layers; each layer has several neurons. Each neuron in each layer is having connection to the neurons in the next layer by weighted coefficients. In general, three types of neuron layers exist in ANN model: the first layer represents inputs, the hidden layer for calculating input weights and the third layer is output layer.

There involve three steps in developing ANN. The first step involves preparation of data for network training. In the second step, different combinations of network structures will be evaluated in order to select the optimal one. The third step involves testing. The ANN utilizes 15% of the data for training, 15% of the data for validation and 70% of the data for testing purpose. The hidden layers and neurons number in every layer are decided by number of iterations by trial and error method. The best network structure which gives minimum error between experimental data and ANN data is selected. The weighted relation of the input components is represented in Equation 5 (Naik and Vinod, 2018).

$$Y_i = f\left(\sum_{m=1}^n W_{mi} X_i + b_m\right) \quad (5)$$

where, Y_i , X_i , and n are the output, input and the number of neurons that connect to the m^{th}

neuron. b_m represents bias and W_{mi} represents weighted coefficient. The field saturation flow values of six signalized intersections are given as target data and cycle time, peak hour volume, proportion of three wheelers and cars are given as input data to ANN. The ANN modelling is implemented in MATLAB. In the present study, six intersections each of four-legged are considered. For each intersection, 30 cycles vehicular volume is extracted for peak hour. The saturation flow value is obtained as the average of above mentioned 30 cycles. Thus, obtaining a single value for each leg. A total 24 saturation values are obtained and is used as input for the ANN model building in MATLAB. Of the input random data points, about 4 (15%) values are used for training the programme, 16 (70%) values are used for testing and remaining 4 (15%) are used for the validation of the ANN model built. One and two hidden layers with number of neurons increased from 1 to 10 for each layer are tried. The final network for estimating saturation flow is optimized at two hidden layers and five neurons ($5 \times 2 \times 1$). Later, with the increase in the number of neurons, the saturation flow is decreasing. The Figure 1 shows the network and Figure 2 shows the output from ANN.

Comparison of Saturation Flow Values

In this section a comparison is made with the help of box plot, among saturation flow rates estimated using ANN and those estimated using MLR and INDO HCM, using field

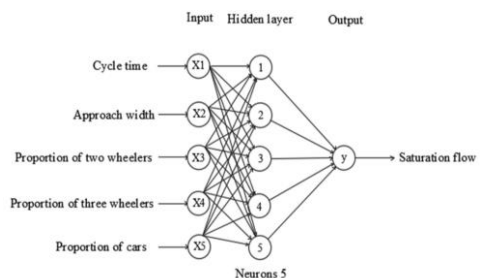


Figure 1. Optimized Artificial Neural Network

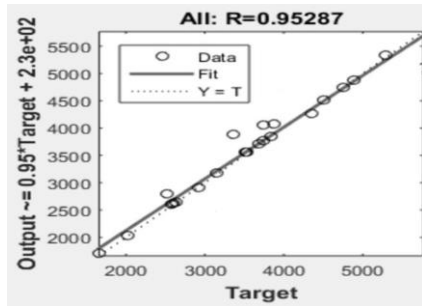


Figure 2. Network output from ANN (MAT lab)

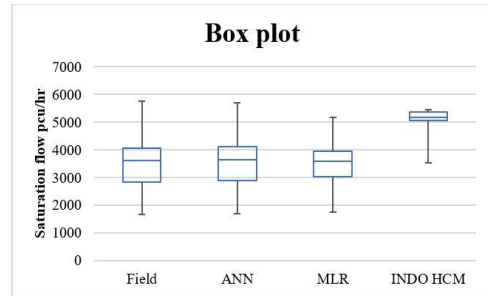


Figure 3. Boxplot showing variation among different methods

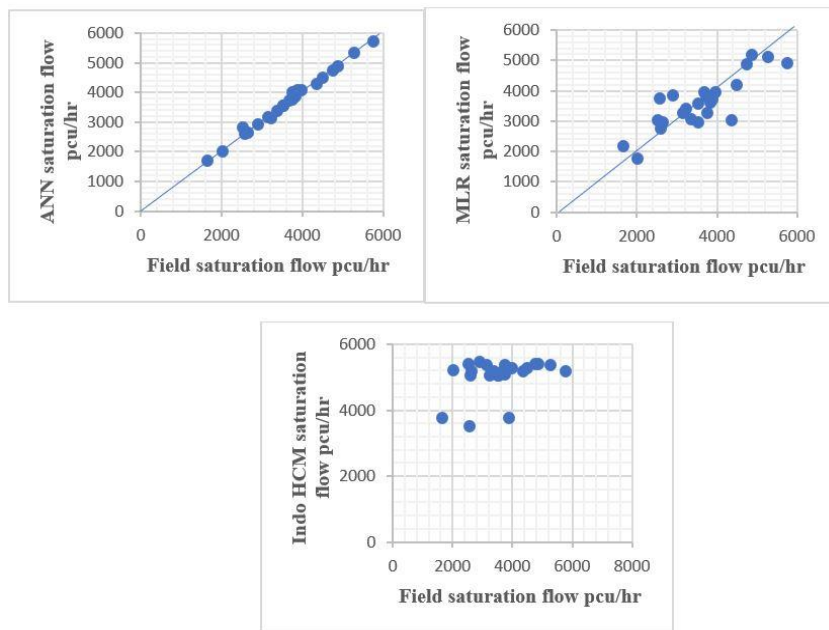


Figure 4. Variation of field saturation flow with respect to MLR, ANN and INDO HCM

saturation flow values obtained from six signalized intersections. Figure 3 shows box plot of saturation flow values using different methods. From the box plot, it is clearly seen that the field saturation flow values are very close to those obtained from ANN than those obtained from MLR and INDO HCM. Graphical representation of the field estimated saturation flow with that obtained using MLR, ANN and INDO HCM are presented in Figure 4.

Accuracy and Error Measurements

Accuracy measurement of the developed models is essential to represent the degree to which the model is corresponding to a real system. MAPE and IA are used for measuring accuracy. MAPE (Equation 6) is useful measure for predicting accuracy of a forecasting method. The Index of Agreement (IA) (Equation 7) was developed by Willmott (1981) useful for

Table 6. Error and accuracy measurements

Model	R ²	Intersection	MAPE (%) for individual intersections	MAPE (%) considering six intersections	IA for individual intersections	IA considering six intersections
ANN	0.95	Eranhipalam	1.78		0.997	
		Kazipet railway station	1.81		0.998	
		Malaparamba	1.79		0.998	
		Kakatiya university cross roads	1.67		0.995	
		Suchitra	1.73	1.76	0.999	0.999
		Thondayad	1.76		0.997	
MLR	0.72	Eranhipalam	9.8		0.93	
		Kazipet railway station	10.8		0.92	
		Malaparamba	7.9		0.89	
		Kakatiya university cross roads	14.8		0.86	
		Suchitra	15.1	11.7	0.93	0.910
		Thondayad	11.9		0.90	
INDO HCM	-	Eranhipalam	34		0.83	
		Kazipet railway station	25		0.92	
		Malaparamba	31		0.87	
		Kakatiya university cross roads	29		0.91	
		Suchitra	27	29	0.89	0.89
		Thondayad	30		0.88	
Kringing Model (Saha <i>et al.</i> , 2018)	0.98	-	1.53			
Hossain (2001)	0.92	-	35			

predicting the degree of accuracy of model prediction, which usually varies between 0 to 1. The IA of 1 indicates perfect match whereas, the IA of zero indicates no agreement at all. The model which is having lowest MAPE and higher IA value is the best prediction.

$$MAPE = \frac{1}{n} \left| \frac{Y_{exp} - Y_{pred}}{Y_{pred}} \right| \times 100 \quad (6)$$

$$IA = 1 - \left[\frac{\sum_{i=1}^n (Y_{pred} - Y_{exp})^2}{\sum_{i=1}^n (|Y_{exp} - \overline{Y_{exp}}| + |Y_{pred} - \overline{Y_{pred}}|)^2} \right] \quad (7)$$

where,

Y_{exp} = field saturation flow values,

Y_{pred} = model saturation flow values,

$\overline{Y_{exp}}$ = mean saturation flow obtained from the field,

$\overline{Y_{pred}}$ = mean saturation flow obtained from ANN,

N = number of observations.

The performance of different models is tabulated in Table 6.

From Table 6, it is observed that, ANN model is very accurate in predicting saturation flow because of its low MAPE and high IA. The calibration and validation of ANN models will be done internally without any human involvement. The accuracy measurement R^2 and MAPE values are in comparison with the Kringing models developed for estimation of saturation model. Authors, Saha *et al.* (2018) have considered the percentage of traffic and the percentage of right turning vehicles. The complexity of Kringing model increase with added parameters with multi dimensionality. While in ANN, the multi variables and the complex relations can be relatively easily iterated internally.

Hossain (2001) estimated saturation flow using regression analysis, at intersection where the traffic is dominated with non-motorized traffic (about 60%). This model may not predict the saturation flow for the urban roads in developing countries like India where two wheelers and cars are more predominant.

Conclusions and Future Scope

In the present study, MLR model and ANN models are developed for estimating saturation flow. Also, the relationship for estimating saturation flow given in INDO HCM is used for comparison purpose. The R^2 value, the MAPE and IA of the multiple linear regression model (MLR) are not satisfactory. Also, Saturation flow obtained using INDO HCM are highly deviated from the field values when compare to that of saturation flow obtained using the developed linear regression equation and ANN. The saturation flow model given in INDO HCM has been developed using the data collected from 18 metropolitan cities where, the land use characteristics, traffic composition and traffic calming measures are different when compare to medium size cities. But, in the present research work, the signalized intersections are selected both from metropolitan and non-metropolitan cities. In the present study, ANN approach is used for estimating saturation flow. The R^2 , MAPE and IA of the ANN model are highly satisfied. Therefore, the ANN models are having the better potential for the prediction of saturation flow and can be used for the estimation of saturation flow at any signalized intersection irrespective of the city size, land use characteristics and traffic compositions. The developed ANN model well predicted the saturation flow and can be used for predicting saturation flow at all signalized intersections. The present study is limited only to four legged intersections and it can be further extended to three legged intersections. Also, Pedestrian phase may be included for further study, if the percentage of pedestrians is high.

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