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Short term traffic flow prediction for a non urban highway using Artificial Neural Network

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Abstract

This study applies Artificial Neural Network (ANN) for short term prediction of traffic flow using past traffic data. The model incorporates traffic volume, speed, density, time and day of week as input variables. Speed of each category of vehicles was considered separately as input variables in contrast to previous studies reported in literature which consider average speed of combined traffic flow. Results show that Artificial Neural Network has consistent performance even if time interval for traffic flow prediction was increased from 5 minutes to 15 minutes and produced good results even though speeds of each category of vehicles were considered separately as input variables.

Keywords: traffic flow; speed; heterogeneous traffic; multi-layer perceptron; sensitivity.

1. Introduction

There has been a steady increase in both rural and urban traffic in recent years resulting in congestion, accidents and pollution. To resolve traffic related problems scientifically and reasonably has become a society-wide consensus. Building transportation infrastructures can relieve the traffic pressure upto a certain level and for a limited period of time only. One of the important way to increase transport efficiency, reduce traffic congestion and improve traffic safety situation, is to implement traffic guidance and control, effectively use the road resource and give full play to vehicle function (Hu et al., 2010). In developing countries where resources are limited and due to less attention paid to transportation sector; traffic congestion problem is becoming a major

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challenge for administrators and planners. As for as Indian condition are concerned, Indian cities are facing traffic problems characterized by mixed traffic flow conditions, levels of congestion, noise and air pollution, traffic fatalities and injuries (Chandra and Kumar, 2003). Pucher et al. (2005) analyzed key trends in India's transport system and travel behavior, investigated extent and causes of the most severe problems, and recommended nine policy improvements for mitigation of India's urban transport crisis. They pointed that India's transport crisis has significantly increased due to rapid growth of larger and medium cities in the context of low incomes, limited and outdated transport infrastructure, rampant suburban sprawl, sharply rising motor vehicle ownership and use, deteriorating bus services, a wide range of motorized and non-motorized transport modes sharing roadways, and inadequate as well as uncoordinated land use and transport planning.

Most of the traffic flow prediction models are based on homogeneous traffic flow taking into account average speed of traffic stream which does not seems to be suitable for the heterogeneous traffic (Theja and Vanajakskshi, 2010). To overcome problems associated with mixed (heterogeneous) traffic flow, there is an urgent need to develop models that incorporate heterogeneous traffic conditions (Khan and Maini, 2000). Models thus obtained will be useful in developing highway and transportation plans, performing economic analysis, establishing geometric design criteria, selecting and implementing traffic control measures, as well as evaluating service quality of transport facilities (Queck et al., 2006). In recent years, Intelligent Transportation Systems (ITS) have achieved great developments. Intelligent Transportation Systems applications are those that improve efficiency of surface transportation systems and solve transportation problems by using modern information and communication technologies. To fulfill increasing traffic demand, there is a need to implement ITS for efficient utilization of transport infrastructure. One of the most important requirements of these systems is the ability to predict the nature of the traffic stream accurately. There are three kinds of data in transportation systems, which are historical data, real-time data and short-term forecasting data. The ability to predict traffic variables such as speed, travel time or flow, based on real time data and historic data, collected by various systems in transportation networks, is vital to the ITS components such as in-vehicle route guidance systems (RGS), advanced traveler information systems (ATIS), and advanced traffic management systems (ATMS) (Zeng et al., 2008). Short-term traffic forecasting is the process of directly estimating anticipated traffic conditions at a future time, given continuous short-term feedback of traffic information. Several diverse modeling efforts have been made to address the problem of short-term traffic forecasting. Due to stochastic nature of traffic flow and highly nonlinear characteristics for short term prediction, artificial intelligence techniques have received much attention and are considered as an alternative for traffic flow prediction model. The literature has shown that neural networks are one of the best alternatives for modeling and predicting traffic parameters since they can approximate almost any function, regardless of its degree of nonlinearity and without prior knowledge of its functional form (Vlahogianni et al., 2005).

Previous studies (Theja and Vanajakskshi, 2010; Celikoglu and Cigizoglu, 2007; Centiner et al., 2010; Sharma et al., 2011; Xiao-li and Guo-guang, 2007 etc.) have considered averaged speed of all vehicles in a combined manner, but it does not seems feasible for mixed type of traffic in developing countries, where slow moving vehicles along with two wheeler, three wheeler and animal driven vehicles constitute a significant part of the traffic flow. Main objective of this study is to investigate the stability and efficiency of neural network for short term prediction of traffic volume in the case of mixed Indian traffic flow conditions. An attempt has been made to model and predict traffic volume of a four Lane Divided Non Urban Highway (National Highway-58) using Artificial Neural Network (ANN) up to 15 minutes in future in contrast to five minutes in the previous study done by Kumar et al. (2013).

2. Literature review

Current practice in traffic management and control strategies is dominated by the emerging use of intelligent transportation systems (ITS), rapid development of fast computers and flexible mathematical methods. The overall objective of such systems is to increase the operational efficiency and capacity of the transportation system through the extensive and multipurposed use of advanced technological and telecommunication systems (Vlahogianni et al., 2004). Prediction of traffic variables such as volume, speed, density, travel time, headways, etc. is important in traffic planning and design operations. Various methods are reported in the literature for prediction of traffic parameters such as time series analysis, real time method, historic method, statistical methods and machine learning etc. It becomes essential to understand working process behind each of these methods to know limitations and advantages associated with them. To overcome the problems associated with historical, data based algorithms and time series models; Smith and Demetsky (1994) applied ANN for short traffic flow prediction. An ANN model for urban traffic flow was presented (Ledoux, 1997). Based on simulated data, one minute ahead predictions of the queue lengths and output flows were obtained with fairly good accuracy. It was emphasized that there is need to further investigate these techniques on experimental data. Short-term inter-urban traffic forecasts using neural networks was investigated by Dougherty and Cobbett (1997). Neural network models using back-propagation were trained to make short-term forecasts of traffic flow, speed and occupancy in the Utrecht/Rotterdam/Hague region of Netherlands. Kirby et al. (1997) performed a comparative study between neural networks and statistical models for short-term motorway traffic forecasting.

To check the effectiveness of a neural network system for prediction based on time-series data, Yasdi (1999) employed artificial neural networks for traffic forecasting on a road section. Performance of recurrent Jordan network was examined in the study. Simulation results demonstrate that learning with this type of architecture has a good generalisation ability. Dia (2001) applied an object oriented neural network approach for short-term traffic forecasting. Their approach provides a sound basis for modeling complex interactions such as mixing supervised and unsupervised learning rules in the same network or incorporating a recurrent processing element into hidden layer of a feed forward topology without the need for deriving new learning equations. An advanced, genetic algorithm based, multilayered structural optimization strategy that can assist both in the proper representation of traffic flow data with temporal and spatial characteristics as well as in the selection of the appropriate neural network structure was invented by Vlahogianni et al. (2005). Further, the performance of the developed network was tested by applying it to both univariate and multivariate traffic flow data from an urban signalized arterial. Results show that the capabilities of a simple static neural network, with genetically optimized step size, momentum and number of hidden units, are very satisfactory when modeling both univariate and multivariate traffic data. On the other hand Jiang et al. (2005) developed dynamic wavelet neural network model for traffic flow forecasting for capturing the dynamics of the traffic flow and for pattern recognition with enhanced feature detection capability.

A neural network model was introduced (Zheng et al., 2006) that combines the prediction from single neural network predictors according to an adaptive and heuristic credit assignment algorithm based on the theory of conditional probability and Bayes' rule. Two single predictors, i.e., the back propagation and the radial basis function neural networks were designed and combined linearly into a Bayesian combined neural network model. The credit value for each predictor in the combined model was calculated according to the proposed credit assignment algorithm and largely depends on the accumulative prediction performance of these predictors during the previous prediction intervals. For experimental test, two data sets comprising traffic flow rates in 15-min time intervals were collected from Singapore's Ayer Rajah Expressway. It was found that most of the time, combined model outperforms the singular predictors.

Two comparative studies were reported using two different ANN architectures, feed forward back-propagation (FFBP) versus radial basis function (RBF) (Celikoglu and Cigizoglu, 2007) and feed forward back-propagation (FFBP) versus generalized regression neural network (GRNN) (Celikoglu and Cigizoglu, 2007) for the purpose of daily trip flow forecasting. It was found that RBF neural network and GRNN did not provide negative forecasts in contrast to FFBP networks. To overcome the problems such as complexity of the traffic historical data and the randomness of lots of uncertain factors, a hybrid predicting model that combines both Autoregressive Integrated Moving Average (ARIMA) and Multilayer Artificial Neural Network (MLANN) was studied by Zeng et al. (2008). Experimental results with real data sets indicate that the combined model can be an effective way to improve forecasting accuracy achieved by either of the models used separately.

Theja and Vanajakskshi (2010) investigated the application of Support Vector Machines (SVM) for short term prediction of traffic parameters, namely speed, space headway and volume under heterogeneous traffic conditions. Sensitivity analysis was performed to find optimum parameters of support vector regression (SVR) in terms of accuracy and running time. Comparison of performance was carried out between SVM and the multi-layer feed forward neural network with back propagation. Recent studies (Centiner et al., 2010; Hu et al., 2010; Pamula, 2011) applying different ANN architectures with different input parameters measured through field studies by using advanced instruments demonstrate that ANN modeling is an effective approach for short term traffic flow modeling. A novel neural network (NN) training method that employs the hybrid exponential (EXP) smoothing method and the Levenberg–Marquardt (LM) algorithm was developed by Chan et al. (2012), which aims to improve the generalization capabilities of previously used methods for training NNs for short-term traffic flow forecasting. The proposed method was evaluated by forecasting short-term traffic flow conditions on the Mitchell freeway in Western Australia. Results indicate that, in general, test errors obtained by EXP-LM are smaller than those obtained by the other tested algorithms. It was concluded that NNs with superior generalization capabilities for traffic flow forecasting can be obtained by using EXP-LM.

3. Data collection

Data used in the present paper has been taken from previous study by Kumar et al. (2013). This data were collected from Muzaffarnagar bye-pass, on National Highway-58 (NH-58), Km 115.000 from Roorkee to Delhi, Uttar Pradesh, India at two selected locations (at 116.500 and 128.700). NH-58 is a four lane divided national highway from Delhi to Muzaffarnagar and remaining stretch is two lane. It has 7.0 m main carriageway with 1.5 m paved shoulder and 2.0 m earthen shoulder on both sides with the median having length of 4.2 m. It is one of the important national highways in north India, connecting Delhi to northern hill areas cities like Roorkee, Haridwar, Rishikesh, Joshimath, Badrinath etc. Data samples were collected using video cameras at selected locations for a period of five days from Monday to Friday between 11.00 am to 1.00 pm.

4. Data extraction

Data extraction was carried out in the intervals of 15 minutes (Table 1) for both directions using FMV6 (Full Motion Video) player. Vehicles were classified in eight categories namely Car/Jeep/Van, Scooter/ Motorcycle, Light Commercial Vehicle (LCV)/Minibus, Bus, Truck, 3-wheeler, Tractor trailor and Horsecart/Bullockcart/other animal drawn vehicles. Traffic volume data were extracted manually by counting number the vehicles crossing a fixed section of road on the video. Thus 8 data sets were generated on each location for a period of two hour. Since data were collected at two selected locations for the period of two hours at each location, 32 data sets were obtained on each day by considering both sides of the road separately (i.e. 8 data sets on each side). Thus 160 data sets were obtained for the period of five days. Average time taken by each vehicle type to travel the trap length was measured by time displayed on video screen with an accuracy of 0.01 s. Entry and exit time of vehicles at beginning and end points of the trap were tabulated as in-time (T1) and out-time (T2). Speed of each vehicle category in both directions was calculated by operating on time difference values (T1-T2) and trap length (35 m). The extracted data were entered in MS Excel sheet for further analysis.

5. Traffic flow prediction using ANN

5.1 *ANN methodology*

Same ANN methodology has been used in this study as by Kumar et al. (2013). Neural networks are empirical

Table 1. Summary of traffic volume and speed measurement for 15 minutes interval at the selected location

	Delhi-Haridwar								Haridwar-Delhi							
	Volume				Average Speed (Km/hour)				Volume				Average Speed (Km/hour)			
Vehicle Category	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD
C/J/V	13	71	37.75	20.86	71.5	78	75.56	2.11	14	57	41.13	14.14	71.5	78	75.18	2.15
S/M	25	53	33.25	13.28	55	59	57	1.58	16	48	29.25	14.17	52.5	60	57.75	3.57
LCV/M	0	3	1.75	1.5	60	66	63.4	2.19	1	6	3	2.44	62	66	64.33	1.86
B	2	8	5	3.46	49.5	53	51.21	1.46	2	8	5	2.58	49.5	52.5	51.28	1.04
T	8	21	13	5.59	53	57	55.57	1.24	8	18	14.75	4.72	55.5	60	56.75	1.46
TW	0	1	0.75	0.5	33	34.5	33.5	0.86	0	5	1.75	2.36	35.5	39	37.33	1.76
T/T	1	5	2.75	1.71	28	32	30.36	1.97	0	5	1.75	2.22	29.5	32	31	1.32
H/B	1	2	1.25	0.5	6.23	9.25	7.54	1.46	0	3	1.25	1.5	7.24	8.32	7.76	0.59

(data-driven), self-adaptive models that have the ability to capture the underlying relationships without the need of a priori assumptions regarding the problem examined (Zhang et al., 1998). They have ability to learn from data, even if the underlying relationships are not apparent, their non-linear nature and their ability to generalize (after being trained to a sample data they can generate predictions from a part of the data that had not been used for training), makes them a useful tool for working with databases with noise (Vlahogianni et al., 2005). In ANN modeling there is no restriction on the number of variables i.e. one can choose desired number of input or output variables depending on the problem. Till now there exists no general methodology for design of neural networks architecture. Generally a trial and error approach is used. For network generation one can use his/her intuition for design of overall network structure. Important features which are of concern for the design of neural network include structure of the network, number of input variables, number of hidden layers, activation or transfer function and selection of learning or training algorithm (Sivanandam et al., 2010).

5.2 ANN modeling and network architectures

Multilayer perceptron (MLP) network has been used for prediction of traffic flow data 15 minutes in future using past 45 minutes data. 160 data sets have been taken for analysis, each of which contains 19 features. Day of week, time of day, category of vehicles divided in 8 parts, corresponding average speed of vehicles divided in 8 parts and traffic density were among these features as shown in Table 2. Whole database was divided into three parts for training, cross validation and testing in the ratio 60, 15, 25 percent respectively. First 45 minutes data (extracted in intervals of fifteen minutes) of each hour were used for training/validation stage and last 15 minutes data for testing purpose. Thus 96, 24, 40 data sets were used for training, cross validation and testing the ANN models respectively.

Trial and error approach has been used to obtain best performing network architecture. Ten ANN models with different number of hidden neurons were constructed and trained using same set of training data. Networks were trained; cross validated and tested using the Neuro Solution software version 6.0. Minimum MSE was taken as stopping criterion during training of network. Details of networks with different architectures used to determine the desired network has been illustrated in Table 3. Performances of the ANN models were evaluated using cross validation and testing data sets. Mean square error (MSE), mean absolute error (MAE), normalized mean square error (NMSE) and coefficient of correlation (r) were used to evaluate prediction results. From the Table 3 it is clear that neural network with six hidden neurons produces the best prediction. Thus used ANN structure in the present study has 19 inputs, 6 neurons in hidden layer and single output, which is shown in Fig. 1.

Table 2. List of input variables considered for ANN modeling

S. No.	Variables	Abbreviation	S. No.	Variables	Abbreviation
1	Day of week	DY	11	Average speed of Car/Jeep/Van	SCJV
2	Time of day	TM	12	Average speed of Scooter/Motorcycle	SSM
3	Number of Car/Jeep/Van	C/J/V	13	Average speed of Mini Bus/LCV	SLCV
4	Number of Scooter/ Motorcycle	S/M	14	Average speed of Bus	SB
5	Number of LCV/ Minibus	LCV/M	15	Average speed of Truck	ST
6	Number of Bus	B	16	Average speed of 3-Wheeler	STW
7	Number of Truck	T	17	Average speed of Tractor/Trailor	STT
8	Number of 3-Wheeler	TW	18	Average speed of Horsecart/Bullockcart	SHB
9	Number of Tractor/Trailor	T/T	19	Traffic density	Density
10	Number of Horsecart/Bullockcart	H/B			

Table 3. Details of networks with different architecture

Trial No	Train 1	Train 2	Train 3	Train 4	Train 5	Train 6	Train 7	Train 8	Train 9	Train 10
No. of hidden layers	1	1	1	1	1	1	1	1	1	1
Number of hidden neurons	3	4	5	5	6	3	3	4	5	6
Transfer Function	Sigmoid	Sigmoid	Sigmoid	Tanh Axon	Sigmoid	Sigmoid	Tanh Axon	Sigmoid	Tanh Axon	Sigmiod
Number of epochs	300	400	500	500	700	300	300	400	500	600
Learning	Moment-um	Moment-um	Moment-um	Momentum	Moment-um	Leven-berg	Levenberg	Leven-berg	Levenberg	Levenberg
Step Size/ Momentum	1/0.7	1/0.7	1/0.7	1/0.7	1/0.7	-	-	-	-	-
Minimum MSE (T)	0.0194	0.0093	0.0096	0.0057	0.0125	6.42 E-05	0.0015	0.0005	0.0007	5.23 E-06
Final MSE (T)	0.0194	0.0093	0.0096	0.0057	0.0125	6.42 E-05	0.0018	0.0011	0.0048	5.23 E-06
Minimum MSE(X)	0.0262	0.0164	0.0099	0.0088	0.0099	0.0001	0.0016	0.0004	0.0012	1.92 E-05
Final MSE (X)	0.0262	0.0164	0.0099	0.0088	0.0099	0.0004	0.0024	0.0004	0.0012	1.96 E-05
MSE (Y)	2197.81	1084.70	1159.06	155.67	1372.29	34.61	57.98	47.02	50.84	8.51
NMSE (Y)	0.9242	0.3960	0.4922	0.0827	0.6087	0.0098	0.0235	0.0228	0.0214	0.0034
MAE (Y)	37.6309	25.5408	25.6473	10.2711	28.6656	4.2588	6.0786	5.0415	5.8149	1.2786
r (Y)	0.7678	0.8802	0.8198	0.9589	0.8258	0.9977	0.9892	0.9906	0.9914	0.9984

T= During training stage, X= During cross validation, Y= During testing stage, RMSE=Root Mean Square Error, r =coefficient of correlation

5.3 Sensitivity analysis

Sensitivity is defined as mathematical expectation of output deviation due to expected input deviation with respect to overall input patterns in a continuous interval (Yeung et al., 2010). It refers how a networks output is influenced by its input and/or weight perturbations. Sensitivity analysis is performed on a trained network to find and eliminate irrelevant inputs. Elimination of irrelevant inputs reduces data collection cost and can improve the network's performance. It gives some insight into the underlying relationships between the inputs variables and the output also. ANN model (train 10) was used for sensitivity analysis. Sensitivity analysis was performed about the mean on the pre-trained MLP network. This batch starts by varying the first input between its mean +/- 5 while all other inputs were kept fixed at their respective means. The network output was computed for hundred steps above and below the mean. This process was then repeated for each input variable.

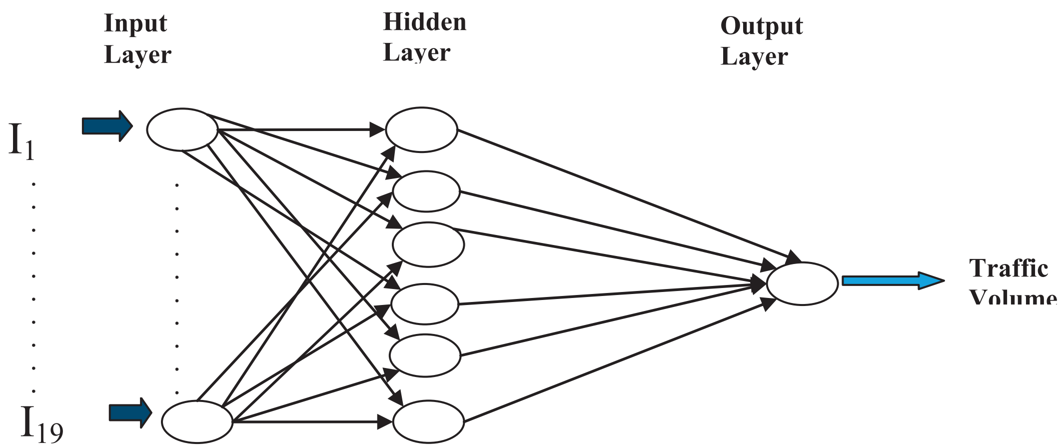

Fig. 1. ANN architecture for best network

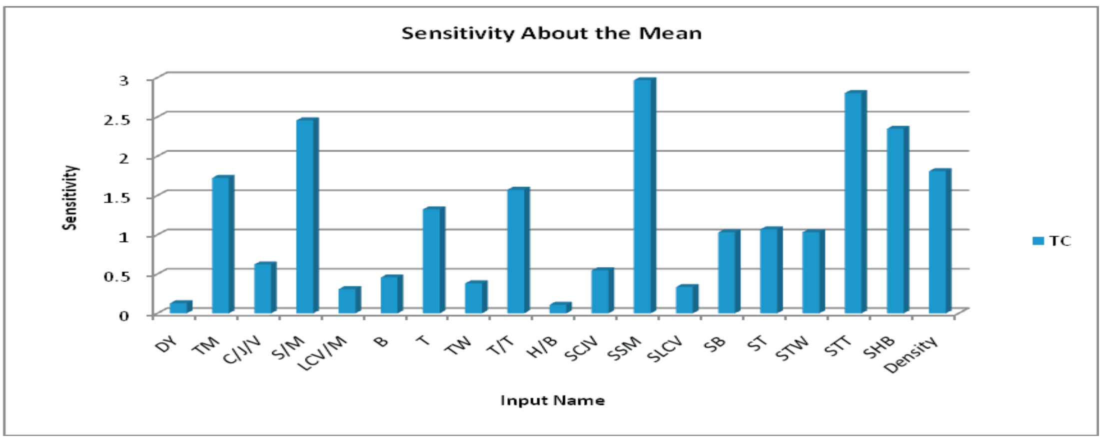

Fig. 2. Sensitivity analysis of input variables with respect to the output about their mean values TC=Traffic Count (Traffic Volume)

Table 4. Comparison between best ANN model (Train 10) and sensitivity model

Parameters	Minimum MSE (T)	Final MSE (T)	Minimum MSE(X)	Final MSE (X)	MSE (Y)	NMSE (Y)	MAE (Y)	r(Y)
Train 10	5.23 E-06	5.23 E-06	3.33 E-05	1.92 E-05	8.5138	0.0034	1.2786	0.9984
Sensitivity model	0.00268	0.00268	0.0057	0.0057	355.82	0.0624	15.174	0.9741

Results of sensitivity analysis show that nine most significant inputs parameters are speed of Scooter/Motorcycle (SSM), speed of Tractor/Trailor (STT), number of Scooter/Motorcycle (S/M), speed of Horsecart/Bullockcart (SHB), traffic density, time (TM), number of Tractor/Trailor (T/T), number of Trucks (T) and speed of Truck (ST) (as presented in Fig. 2). In the next step neural network was trained and tested with same ANN configuration as in the best performing ANN model (train 10) considering only 9 most significant input parameters found in the sensitivity analysis. Results for training, cross validation and testing stage of the new model are described in Table 4. It is obvious from the results that this new model performs well compared to the best performing ANN model (train 10) even after reducing number of inputs from 19 to 9.

6. Results and discussion

Graph between observed (measured) and predicted (simulated) values (by ANN Model) for testing stage is shown in Fig. 3. To check performance of the developed model, χ^2 -test was applied. χ^2 -test value of the model at 5% level of significance comes 1.892, which is less than 54.572 (critical value at 39 degrees of freedom). Since calculated χ^2 -value is less than critical χ^2 -value, therefore using null hypothesis it was concluded that mean values of measured traffic volume and predicted ones do not differ significantly. Present model incorporates the average speed of all vehicle categories separately as input variables to deal with realistic conditions of heterogeneous (mixed) traffic. From Table 5, it is clear that present model gives almost similar results even if the time interval was taken as 15 minutes as compared to 5 minutes in the previous study by Kumar et al. (2013). Results reveal that ANN has consistent and stable performance irrespective of increase in time interval for traffic flow prediction with less number of data sets available for training, cross validation and testing.

Although, ANN modeling has many advantages in comparison to analytical and statistical techniques. But, still there are some issues related to ANN modelling also. One of the major limitations associated with ANN modeling is its black box type nature. In time series modeling and fuzzy logic we can find cause and effect of each of independent variable, but in ANN framework same is not possible. It is not possible to find the mutual interrelation between the variables in ANN modeling.

Major limitations of the study include vehicle composition quality of traffic flow during off peak hours only. Hourly variation in 24 hours traffic system does not come under the umbrella of this study. Other limitation is that data consist only day time traffic flow characteristics i.e. night time traffic flow characteristics are not taken into consideration. Since two-hour traffic survey presents only a small view of traffic flow properties of the composition observed during stipulated period. Traffic flow is a dynamic process and it keeps changing over time to time and place to place. It depends upon various factors like weather, festival season, accidents, local characteristics and driver's behaviour (Sharma et al., 2013). Therefore it can happen that observations made between two different periods of the study may not give exactly the same results. Data sets used in this study only present flow regimes for an uninterrupted traffic

Table 5. Comparison of performance between ANN models developed for 15 minutes (Train 10) and 5 minutes (Kumar et al. (2013))

ANN model	No. of data sets used in modelling	r	RMSE	MAE	Standard Deviation (SD)
For 15 Minutes	160	0.9984	2.9178	1.2786	2.8711
For 5 Minutes	480	0.9988	0.8586	0.6281	0.8573

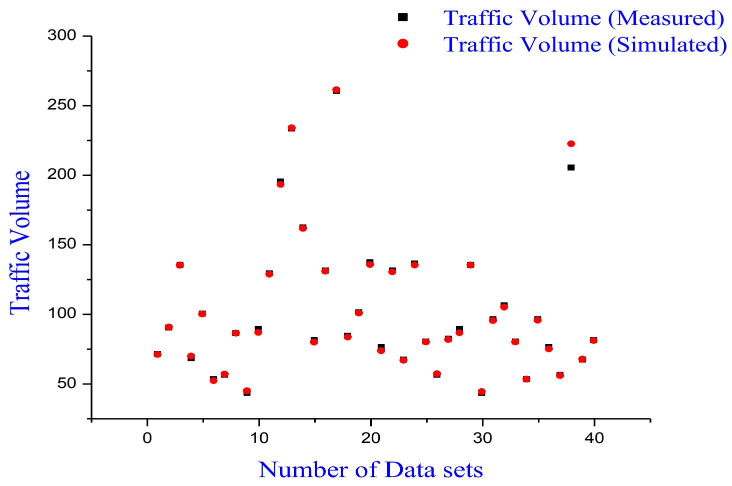

Fig. 3. Measured and predicted (simulated) traffic volume (by ANN) for testing stage

traffic flow condition. Other parameters like weather condition, seasonal variation in traffic flow and extreme condition (like accident or traffic jam) have not been taken into consideration in the present study. Since data considered in this study consists only off-peak hours traffic which does not represent total variability in the traffic flow. Future study will focus on collection of data sets for longer period of time to cover all possible realistic conditions associated with traffic flow.

7. Conclusion

In this study, a neural network based model for short term prediction of traffic volume for non urban highway in heterogeneous condition has been presented. Results clearly indicate that ANN model was able to predict vehicle count accurately even if vehicles category and their corresponding speeds were considered separately as input variable. It is quite obvious that ANN has consistent performance even if time interval for prediction has been increased. Therefore it is concluded that ANN can be applied for short term traffic flow prediction with mixed traffic conditions for non urban Indian highways.

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