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SHORT TERM TRAFFIC FLOW PREDICTION IN HETEROGENEOUS CONDITION USING ARTIFICIAL NEURAL NETWORK

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Abstract. Traffic congestion is one of the main problems related to transportation in developed as well as developing countries. Traffic control systems are based on the idea to avoid traffic instabilities and to homogenize traffic flow in such a way that risk of accidents is minimized and traffic flow is maximized. There is a need to predict traffic flow data for advanced traffic management and traffic information systems, which aim to influence traveller behaviour, reducing traffic congestion and improving mobility. This study applies Artificial Neural Network for short term prediction of traffic volume using past traffic data. Besides traffic volume, speed and density, the model incorporates both time and the day of the week as input variables. Model has been validated using actual rural highway traffic flow data collected through field studies. Artificial Neural Network has produced good results in this study even though speeds of each category of vehicles were considered separately as input variables.

Keywords: artificial neural network; traffic flow; intelligent transportation system; modelling; speed.

Introduction

Roads are an essential part of infrastructure and traffic that flows through them determines the economic growth of a country. Traffic studies are important for acquiring knowledge about vehicular flow characteristics. Information obtained through these studies assists in building efficient road facilities and to avoid traffic jams with reduction in travel time. With urbanization and corresponding increase in number of vehicles in metropolitan as well as suburban cities, problem related to traffic congestion is increasing day by day. In rapid developing countries like India, where less attention has been paid to transportation sector and due to mixed traffic, traffic congestion problem is becoming a major challenge for administrators and planners. Indian cities face traffic problems characterized by levels of congestion, noise and air pollution, traffic fatalities and injuries. India's transport crisis has increased due to extremely rapid growth of larger and medium cities in the context of low incomes, limited and outdated transport infrastructure, rampant suburban sprawl, sharply rising motor vehicle ownership and use, deteriorating bus services, a wide range of motorized and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. Pucher *et al.* (2005) presented an article which summarizes key trends in India's transport system and travel behavior, analyzed extent and causes of the most severe problems, and recommended nine policy improvements for mitigation of India's urban transport crisis. 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. Among these approaches, neural network techniques have been commonly applied for the problem (Dougherty 1995). Therefore, to overcome problems associated with mixed (heterogeneous) traffic flow, there is an urgent need to develop models that incorporate heterogeneous traffic conditions (Khan, Maini 1999). 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

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as evaluating service quality of transport facilities. In addition, these models are useful to traffic engineers for transportation planning. There are three fundamental macroscopic traffic variables for a traffic stream, namely traffic volume, speed and density. Ability to predict these variables helps to understand nature of changes that can occur in the transportation networks and thereby helps in mitigating congestion and accidents. Up to authors knowledge most of the traffic flow prediction models are based on homogeneous traffic flow in urban areas taking into account average speed of traffic stream which does not seems to be suitable for the heterogeneous traffic.

The key objective of this study is to investigate if a neural network can be used for the short term prediction of traffic volume in case of Indian conditions, where most of the traffic is mixed type. In this paper 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 five minutes in future by considering speed of each category of vehicles as input variables in contrast to previous studies reported in literature which consider average speed of combined traffic flow. Organization of the paper is as follows. Section 1, provides a brief summary of previous studies. In Section 2 and 3, we discuss about data collection through field measurements and its analysis. Basic theory of ANN and neural modeling for traffic flow prediction along with sensitivity analysis of best neural network has been presented in Section 4. Section 5, describes result for neural network models during training, cross validation and testing stages, also comparison of network's results with those of the measured one and possible directions for future work. We conclude with the statistical robustness of our model in final section.

1. Literature Survey

Prediction of traffic variables such as volume, speed, density, travel time, headways, etc. is important in traffic planning and design operations. Short term prediction of these variables plays a very important role in Intelligent Transportation System (ITS) applications. Different methods are reported in literature for the prediction of traffic parameters such as real time method, time series analysis, statistical methods, historic method, machine learning. It is essential to understand working process behind each of these methods to know limitations and advantages of using them. Literature survey was carried out to investigate use of ANN for traffic flow prediction cited in literature. An artificial neural network is one of the most popular methods reported for short term traffic prediction. An urban traffic flow model using neural network was presented (Ledoux 1997). Based on simulated data, it was concluded on the potentials of neural networks applied to traffic flow modelling. One minute ahead predictions of the queue lengths and the output flows were obtained with fairly good accuracy. It was emphasized that there is need to further investigate these techniques on experimental data.

Dougherty and Cobbett (1997) investigated short-term inter-urban traffic forecasts using neural networks. Back-propagation neural networks were trained to make short-term forecasts of traffic flow, speed and occupancy in the Utrecht/Rotterdam/Hague region of Netherlands. A comparative study between neural networks and statistical models for short-term motorway traffic forecasting was reported (Kirby *et al.* 1997). Dia (2001) presented an object oriented neural network approach for short-term traffic forecasting. This approach provides 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. Two comparative studies were presented using two different ANN algorithms, Feed Forward Back-Propagation (FFBP) versus Radial Basis Function (RBF) (Celikoglu, Cigizoglu 2007a) and FFBP versus Generalized Regression Neural Network (GRNN) (Celikoglua, Cigizoglu 2007b) for the purpose of daily trip flow forecasting. It was observed that RBF neural network and GRNN did not provide negative forecasts in contrast to FFBP applications. Besides, local minima problem faced by some FFBP algorithms, it was not encountered in RBF and GRNN networks. A combined approach based on Principal Component Analysis (PCA) and Combined Neural Network (CNN) for short-term traffic flow forecasting was reported (Zhang, He 2007). PCA not only reduces dimension of input variables and the size of CNN, but also reserves the main information of original variables and eliminates relativity among them. Forecast results show that this approach is better than typical error Back-Propagation Neural Network (BPNN) with same data. Theja and Vanajakshi (2010) investigated the usefulness of Support Vector Machines (SVM) for short term prediction of traffic parameters, namely speed, space headway and volume under heterogeneous traffic conditions. A sensitivity analysis was carried out to find optimum parameters of Support Vector Regression (SVR) in terms of accuracy and running time. A comparison of performance was carried out with a multi-layer feed forward neural network with back propagation. Recent studies (Gao, Sun 2010; Çetiner *et al.* 2010; Pamuła 2011; Dunne, Ghosh 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 traffic flow modelling.

2. Data Collection

Data were collected from Muzaffarnagar bye-pass, on National Highway–58 (NH–58), 115.000 km from Roorkee to Delhi, Uttar Pradesh, India at two selected locations (at 116.500 and 128.700) – see Table 1. Features measured at each section are presented in Table 1. The mid-block section near selected locations was straight with clear sight distance and free from intersections having no traffic restrictions. NH–58 is a four lane divided national highway (Fig. 1) from Delhi to Muzaffarnagar

Table 1. Data set organization

Survey number	Date	Time duration of survey [h]	Distance [km]	Direction	Width of section [m]	Pavement type
1	10 September 2012	2	116.500	Delhi–Haridwar	7.0	Dense asphalt
		2	128.700	Haridwar–Delhi	7.0	Dense asphalt
2	11 September 2012	2	116.500	Delhi–Haridwar	7.0	Dense asphalt
		2	128.700	Haridwar–Delhi	7.0	Dense asphalt
3	12 September 2012	2	116.500	Delhi–Haridwar	7.0	Dense asphalt
		2	128.700	Haridwar–Delhi	7.0	Dense asphalt
4	13 September 2012	2	116.500	Delhi–Haridwar	7.0	Dense asphalt
		2	128.700	Haridwar–Delhi	7.0	Dense asphalt
5	14 September 2012	2	116.500	Delhi–Haridwar	7.0	Dense asphalt
		2	128.700	Haridwar–Delhi	7.0	Dense asphalt

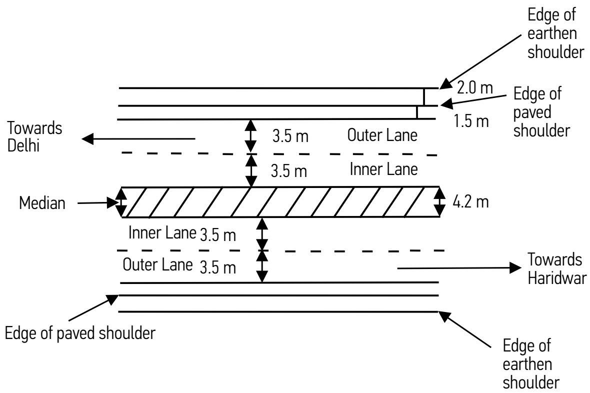

Fig. 1. Four lane divided road section at selected site of National Highway–58

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 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.

3. Data Extraction

Video cameras were mounted on stand and were placed away from road in order not to influence the operating speeds of vehicles and were sufficiently high so as to cover the total trap length. Vehicle movement was assumed to be smooth having no changes of direction. Timer in the each camera was switched on. Recorded film was replayed on a large screen television in the Departmental laboratory to extract the desired information.

Vehicles were classified in eight categories (Car / Jeep / Van, Scooter / Motorcycle / Light Commercial Vehicle (LCV) / Minibus, Bus, Truck, 3-wheeler, Tractor Trailer, Horse-Cart / Bullock-Cart / Other Animal Drawn Vehicles).

Traffic volume data were extracted manually by counting number the vehicles crossing a fixed section of road on the video.

Average time taken by each vehicle type to travel the trap length was measured by time displayed on screen with an accuracy of 0.01 s.

Speed was calculated by measuring the time taken by a vehicle to travel trap length marked on the road.

Entry and exit time of vehicles at beginning and end points of the trap were tabulated as in-time (T1) and out-time (T2). Speeds of each vehicle category in both directions were calculated by operating on time difference values (T1–T2) and trap length. Measured data from survey locations were organized according to the sequence followed by De Luca and Dell'Acqua (2012) as shown in Table 2. Data extraction was carried out in the intervals of 5 minutes (Table 3) for both directions.

Thus 24 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, 96 data sets were obtained on each day by considering both sides of the road separately (i.e. 48 data sets on each side).

In this way 480 data sets were obtained for the period of five days. The extracted data were entered in *Microsoft Excel* sheet for further analysis.

4. ANN Approach for Traffic Flow Prediction

4.1. Artificial Neural Network

ANNs are a computational model that simulates structural and functional aspects of biological neural networks. All neural networks share some basic features. They are composed of simple processing elements, known as neurons. These elements take data from source as input and compute an output dependent in some well-defined way on the values of inputs, using an internal transfer (i.e. activation) function. These neurons are joined together by some weights. Data flows along these connections and is scaled during transmission according to values of weights as shown in Fig. 2.

Table 2. Data set processing

Number of vehicle	Vehicle type	Average vehicle dimensions (Chandra, Kumar 2003) Length [m]	Average vehicle dimensions (Chandra, Kumar 2003) Breadth [m]	Direction	T1 [H:M:S:FS]	T2 [H:M:S:FS]	(T2–T1) [seconds]	Trap length [m]	Speed [km/h]
1	C / J / V	3.72	1.44	Delhi–Haridwar	11:01:10:04	11:01:11:70	1.66	35	75.9
				Haridwar–Delhi	11:01:05:16	11:01:06:85	1.69	35	74.55
2	S / M	1.87	0.64	Delhi–Haridwar	11:04:14:10	11:04:16:45	2.35	35	53.61
				Haridwar–Delhi	11:03:08: 23	11:03:10: 44	2.21	35	57
3	LCV / M	6.1	2.1	Delhi–Haridwar	11:10:08: 43	11:10:10: 43	2.00	35	63
				Haridwar–Delhi	11:15:08: 36	11:15:10: 29	1.93	35	65.3
4	B	10.1	2.43	Delhi–Haridwar	11:02:56: 44	11:02:58: 88	2.44	35	51.63
				Haridwar–Delhi	11:05:28: 13	11:05:30: 67	2.54	35	49.6
5	T	7.5	2.35	Delhi–Haridwar	11:02:18: 13	11:02:20: 34	2.21	35	57
				Haridwar–Delhi	11:04:19: 52	11:04:21: 77	2.25	35	56
6	TW	3.2	1.4	Delhi–Haridwar	11:07:14: 45	11:07:18: 10	3.65	35	34.52
				Haridwar–Delhi	11:11:38: 33	11:11:41: 61	3.28	35	38.41
7	T / T	7.4	2.2	Delhi–Haridwar	11:12:08: 23	11:12:12: 51	4.28	35	29.4
				Haridwar–Delhi	11:09:48: 53	11:09:52: 53	4.00	35	31.5
8	H / B	4.55	1.65	Delhi–Haridwar	11:04:11: 09	11:04:26: 34	15.25	35	8.26
				Haridwar–Delhi	11:08:27: 53	11:08:48: 81	21.28	35	5.92

Notes: H – hour; M – minute; S – second; FS (Fraction of Second) – one hundredth of a second.

Table 3. Summary of speed and traffic volume measurement for five minutes interval

Vehicle category	Delhi–Haridwar								Haridwar–Delhi							
	Average speed [km/hour]				Volume				Average speed [km/hour]				Volume			
	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD	Min.	Max.	Mean	SD
C / J / V	71.5	78	75.07	1.78	3	33	11.41	6.09	71.5	78.5	74.95	1.97	2	28	14.04	7.29
S / M	52.5	61	57.62	3.36	0	14	4.45	4.89	52.5	61	56.13	3.25	0	26	6	8.02
LCV / M	60	66	64.67	2.06	0	1	0.41	0.5	59.5	67	64	2.63	0	2	0.29	0.55
B	49.5	52.5	51.04	1.34	0	2	0.81	0.73	49.5	53.5	51.83	1.33	0	3	0.79	0.77
T	55.5	60	56.35	1.09	0	10	2.77	2.94	55.5	60.5	57.6	2.08	0	6	1.96	1.62
TW	34.5	35.5	35	0.71	0	1	0.09	0.29	38.5	40	39.17	0.76	0	1	0.13	0.34
T / T	29.5	32	30.21	1.89	0	4	0.55	1.1	27.0	32.5	30.2	2.33	0	2	0.25	0.53
H / B	6.23	9.25	7.91	1.54	0	1	0.14	0.35	5.62	6.2	5.91	0.41	0	2	0.13	0.45

Notes: Min. – minimum; Max. – maximum; SD – standard deviation.

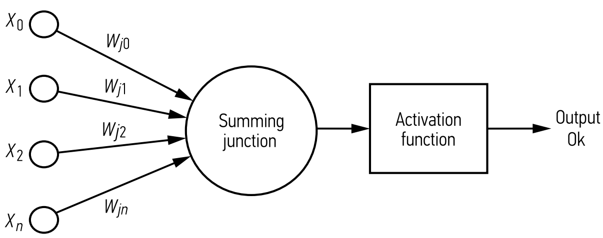

Fig. 2. Nonlinear model of a neuron

Arrangement of neurons into layers and the pattern of connection within and in-between layers are generally called the architecture of the net. The process of modifying weights according to connections between network layers, with the objective of achieving expected output is called training a network. Internal process that takes place when a network is trained is called learning. Generally there are three types of training: supervised, unsupervised and reinforcement. Weight is information used by neural network to solve a problem. Neural networks consist of a large number of processing elements called neurons.

These neurons are connected to each other by directed communication links, which are associated with weights. These weights of connections in the network are altered to produce a desired result. Weights of the connections are optimized using inputs and outputs from training. An activation function is used to calculate the output response of a neuron. The sum of a weighted input signal is applied to activation function to obtain a response. When a new input is given to the trained network, it predicts the output based on its connections and weights. Multi-Layered Feed-Forward (MFFN) are layered feed-forward networks typically trained with static back propagation. Their main advantages are that they are easy to use and that they can approximate any input/output map. MFFN network is one of the extensively used networks (Wu, Zhang 2000). MFFN are layered feed-forward networks typically trained with static back propagation rule, which is one of the most widely used training algorithms. Back-propagation network's learning process consists of four stages (Sivanandam *et al.* 2006):

1. initialization of weights;
2. forward computing of data sets stream;
3. back-propagation of error signals;
4. updating of the weights and biases.

During first stage some small random values are assigned to weights. Original data are transmitted from input layer to output layer through hidden processing layer in the second stage. If the desired output cannot be obtained from output layer, then process of backward propagation takes place in which error signal is propagated backward through the network against the direction of forward computing. During this process, synaptic weights are adjusted in accordance with error signal. The error between network output and desired output is minimized using delta rule by performing these steps iteratively.

Hidden layer neuron activation H_j can be computed as:

$$H_j = f\left(I_j\right);\ I_j = \sum_i W_{ji} X_i, \tag{1}$$

where: W_{ij} – weights from input node i to hidden node j; I_j – value of input node i and $f(\cdot)$ denotes the sigmoid transfer function:

$$f(x) = \frac{1}{1+\exp\left(-\sigma x\right)},$$

where: σ is the steepness parameter.

Output layer neuron activation O_k is given by:

$$O_k = f\left(I_k\right);\ I_k = \sum_j W_{kj} H_j, \tag{2}$$

where: W_{kj} – weights from hidden j node to output node k.

Total error of the neural network is given by:

$$E = \frac{1}{2}\sum_k \left(T_k - O_k\right)^2, \tag{3}$$

where: T_k – target value of output node k for input pattern; O_k – actual value output of node k for input pattern.

Error signal δ_k at output layer and weight adjustment between output to hidden node is computed as:

$$\begin{aligned}&\delta_k = \left(T_k - O_k\right) O_k \left(1 - O_k\right);\\ &W_{kj}\left(\text{new}\right) = W_{kj}\left(\text{old}\right) + \alpha\delta_k H_k + \\ &\mu\left(W_{kj}\left(\text{old}\right) - W_{kj}\left(\text{old}-1\right)\right).\end{aligned} \tag{4}$$

Computation of error signal δ_j at hidden layer and adjustment of weights between hidden and input nodes is given by:

$$\begin{aligned}&\delta_j = H_j\left(1 - H_j\right)\sum \delta_k W_{kj};\\ &W_{ji}\left(\text{new}\right) = W_{ji}\left(\text{old}\right) + \alpha\delta_j X_i + \\ &\mu\left(W_{ji}\left(\text{old}\right) - W_{ji}\left(\text{old}-1\right)\right),\end{aligned} \tag{5}$$

where: α is known as the learning rate which controls speed of convergence to minimum of errors; μ is the momentum rate.

4.2. Model Development

ANN's have many capabilities including flexibility, massive parallelism, learning and generalization ability, accuracy and some amount of fault tolerance in noisy and changing environments. Relationships between different variables are discovered automatically and fitting takes place naturally in a neural network. 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 in ANN modelling. Till date there exists no general theory or method for design of neural networks architecture. Generally a trial and error approach is used. We can use our intuition for design of overall network structure. Complexity of neural network design arises from high order nonlinearity, heterogeneity and high dimension of the problem to be modelled. Basic features which are of concern for the design of neural network include structure of the network, number of input variables, activation or transfer function and selection of learning or training algorithm. All these features are problem specific and generally vary from one model to another. In this study a Multilayer Perceptron (MLP) network has been used for prediction of traffic flow data 5 minutes in future using past 45 minutes data. For network generation day of week, time of day, classified traffic volume (Car / Jeep / Van, LCV / Minibus, Bus, Truck, Scooter / Motorcycle, 3-Wheeler, Tractor / Trailer, Horse-cart / Bullock-cart / Other animal drawn vehicles), corresponding average speed of vehicles and vehicles density were entered in the required format. A set of 480 data records has 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 4. Whole database has been divided into three parts for training, cross validation and testing in the ratio 60, 15, 25% respectively. Each hour's first 45 minutes (extracted in intervals of five minutes) data were used for training/validation and last 15 minutes data for testing stage. Thus 288, 72, 120 data sets were used for training, cross validation and testing the ANN models respectively.

Table 4. Input variables considered by the ANN with their sensitivity about the mean

S. No.	Variables	Abbre-viation	Sensi-tivity
1	Day of week	DY	2.3986
2	Time of day	TM	1.4418
3	Number of Car / Jeep / Van	C / J / V	1.1359
4	Number of Scooter / Motorcycle	S / M	0.3379
5	Number of LCV / Minibus	LCV / M	0.8068
6	Number of Bus	B	0.0503
7	Number of Truck	T	0.6181
8	Number of 3-wheeler	TW	0.1531
9	Number of Tractor/ Trailer	T / T	0.0473
10	Number of Horse-cart / Bullock-cart	H / B	0.1335
11	Average speed of Car / Jeep / Van	SCJV	0.5584
12	Average speed of Two wheeler	SSM	1.6078
13	Average speed of Mini bus / LCV	SLCV	2.3431
14	Average speed of Bus	SB	1.9857
15	Average speed of Truck	ST	0.1083
16	Average speed of 3-wheeler	STW	1.2006
17	Average speed of Tractor / Trailer	STT	0.4763
18	Average speed of Horse-cart / Bullock-cart	SHB	0.5832
19	Traffic density	Density	1.0385

Ten ANN models with different number of hidden neurons were constructed and trained using same set of training data. Performances of these ANN models were compared using cross validation and testing data sets. The Mean Square Error (MSE), Mean Absolute Error (MAE), Normalized Mean Square Error (NMSE) and coefficient of correlation *r* were used to evaluate prediction results. Details of networks with different architectures used to determine the desired network has been illustrated in Table 5. It can be found that neural network with three hidden neurons produces the best prediction. Thus used ANN structure in the present work has 19 inputs, 3 neurons in hidden layer and single output, which is shown in Fig. 3. Network was trained; cross validated and tested using the *Neuro Solution Software* (2012) version 5.0. Minimum MSE was taken as stopping criterion during training of network.

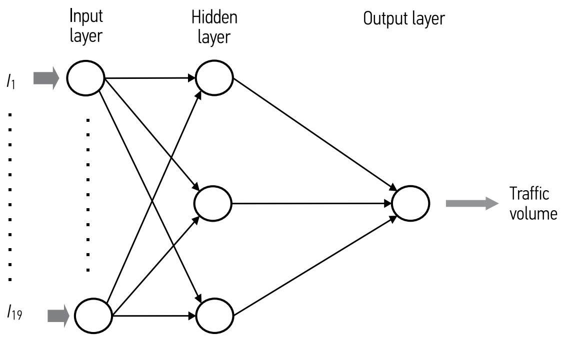

Fig. 3. Structure of neural network

Table 5. 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	4	5	6	8	8	8	8	8	3	4
Transfer Function	Sigmoid	Sigmoid	Sigmoid	Sigmoid	Tanh Axon	Sigmoid	Sigmoid	Tanh Axon	Tanh Axon	Tanh Axon
Number of epochs	500	600	700	1000	1500	1500	2000	2000	300	400
Learning	Momentum	Momentum	Momentum	Momentum	Momentum	Momentum	Momentum	Momentum	Levenberg	Levenberg
Step size / Momentum	1/0.7	1/0.7	1/0.7	1/0.7	1/0.7	1/0.7	1/0.7	1/0.7	–	–
Minimum MSE (T)	0.0122	0.0083	0.0075	0.0025	0.00027	0.00086	0.00071	0.00037	0.00016	0.0005
Final MSE (T)	0.0122	0.0083	0.0075	0.0025	0.00027	0.00086	0.00071	0.00037	0.00017	0.0005
Minimum MSE (X)	0.01764	0.01297	0.01136	0.0039	0.0005	0.0015	0.0013	0.0006	0.00015	0.00072
Final MSE (X)	0.1764	0.01297	0.01136	0.0039	0.0005	0.0055	0.0013	0.0006	0.00015	0.0009
MSE (Y)	246.16886	175.957	168.765	57.8224	2.147423	19.9393	17.8607	2.6316	0.7372	2.5767
NMSE (Y)	0.7433	0.5313	0.5096	0.1746	0.0065	0.0602	0.0539	0.0079	0.0022	0.0077
MAE (Y)	11.3656	9.3699	9.3596	5.4995	1.085	3.1249	2.8854	1.2656	0.6281	1.2105
r (Y)	0.8324	0.8893	0.8875	0.9657	0.9973	0.9828	0.9854	0.9962	0.9988	0.9964

Notes: T – during training stage; X – during cross validation; Y – during testing stage; MSE – Mean Square Error; NMSE – Normalized Mean Square Error; MAE – Mean Absolute Error; *r* – coefficient of correlation.

4.3. Sensitivity Analysis

Sensitivity refers to how a neural network output is influenced by its input and/or weight perturbations. The sensitivity measure 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 is aimed at determining the response of output of the model with variations in input parameters. By performing sensitivity analysis on a trained network we can find and eliminate irrelevant inputs. Elimination of irrelevant inputs reduces data collection cost and can improve the network's performance.

Also, sensitivity analysis gives some insight into the underlying relationships between the inputs variables and the output. In this study the ANN model (train 9) 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 +/–1 while all other inputs were fixed at their respective means. The network output was computed for fifty steps above and below the mean. This process was then repeated for each input.

Table 4 summarizes variation of output with respect to variation of each input. According to sensitivity analysis, nine most important inputs parameters are Day (DY), Speed of Dight Commercial Vehicle (SLCV), Speed of Bus (SB), Speed of Scooter / Motorcycle (SSM), Time (TM), Speed of Two Wheeler (STW), Volume of Car / Jeep / Van (C / J / V), density and volume of Light Commercial vehicle / Minibus (LCV / M) (Fig. 4). In the next step neural network was trained and tested with same ANN configuration as in the best chosen ANN model (train 9) considering only 9 most significant inputs found in the sensitivity analysis. Outputs of training and testing for the new model are presented in Table 6.

This new model performs very well compared to the old model even after reducing number of inputs from 19 to 9.

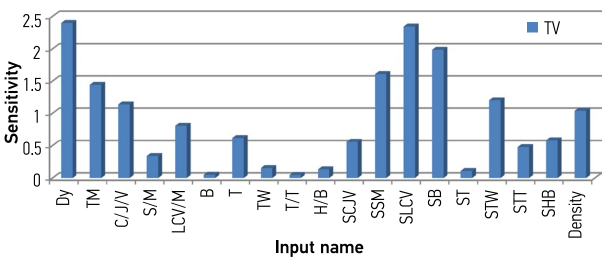

Fig. 4. Sensitivity analysis of considered variables

5. Results and Discussion

Graph between observed (measured) and predicted (simulated) values (by ANN Model) for testing stage is shown in Fig. 5. For validity of the ANN model, calculated Traffic Volume (TV) (by ANN model) was compared with measured traffic volume. Scatter plot for model validation is shown in Fig. 6. Summary of output obtained by ANN modeling process is presented in Table 7. In order to evaluate performance of the developed model, χ^2 -test was applied. χ^2 -test value of the model at 5% level of significance comes 4.1232, which is less than 145.461 (critical value at 119 degrees of freedom).

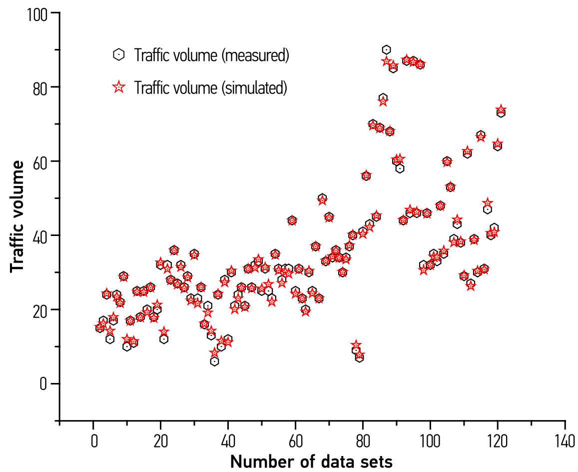

Fig. 5. Measured and predicted (simulated) traffic volume (by ANN) for testing stage

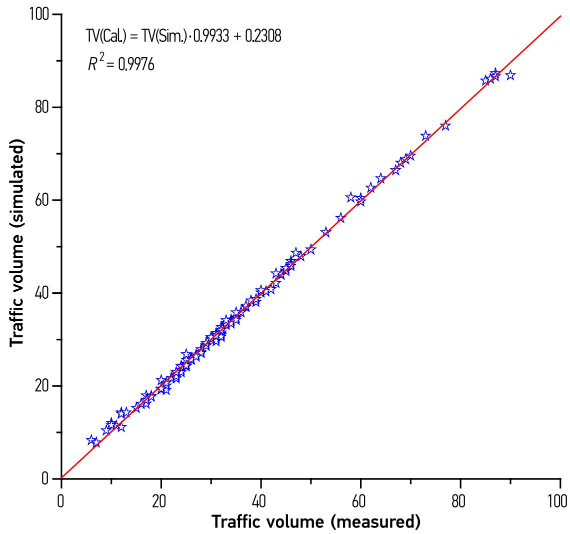

Fig. 6. Linear correlation between measured and simulated traffic volume

Table 6. Comparison between best ANN model (Train 9) 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 9	0.00016	0.00017	0.00015	0.00015	0.7372	0.0022	0.6281	0.9988
Sensitivity model	0.00244	0.00244	0.00389	0.00396	13.871	0.04188	2.981	0.9788

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. Previous studies (Theja, Vanajakshi 2010; Sharma *et al.* 2011; Celikoglu, Cigizoglu 2007a, 2007b; Çetiner *et al.* 2010; Zhang, He 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 like India, where slow moving vehicles along with two wheeler, three wheeler and animal driven vehicles constitute a significant part of the traffic flow. Therefore present model incorporates the average speed of all vehicle categories to deal with realistic conditions of heterogeneous (mixed) traffic. It is obvious that the present model gives accurate results even if the model contains much more input parameters as compared to previous studies, which basically consists of three or four parameters (volume, average speed of all the vehicles combined, density and time of measurement).

ANN learns from examples during training, thus it adjusts weights accordingly and uses this information during cross validation and testing stage. When ANN is trained properly, it produces better prediction results with minimization of errors as compared to analytical and statistical techniques. Besides good value of coefficient of correlation and very small errors, still there exist some problems with ANN modelling. ANN has black box type nature. In time series modelling and fuzzy logic we can find cause and effect of each of independent variable, but in ANN framework same is not possible. Also, in ANN modelling it is not possible to determine the mutual interrelation between the variables.

During data collection, utmost care has been taken to avoid errors. In the present study weather condition, seasonal variation in traffic flow and extreme condition (like accident or traffic jam) have not been taken into consideration. It is not possible in a particular study to include all parameters due to practical and technical limitations associated with data collection process. However, effect of such parameters is yet to be understood in ANN frame work.

Limitations of the study include vehicle composition quality of traffic flow and only off peak hours study period. The two-hour traffic survey presents only a small view of traffic flow properties of the composition observed during stipulated period. Since vehicular traffic flow is a dynamic process and it keeps changing over time to time and place to place. Also, it depends upon various conditions (i.e. weather, festival season, accidents, etc.), local factors and driver's behaviour. Therefore observations made between two different periods of the study may not give exactly the same results. Data sets collected in this study only present flow regimes for an uninterrupted traffic flow condition.

Intelligent Transportation Systems applications are those that improve efficiency of surface transportation systems and solve transportation problems by using modern information and communication technologies. ITS systems like Advanced Traveller Information Systems (ATIS) and Advanced Traffic Management Systems (ATMS) have been deployed in few Indian cities like Pune and Hyderabad (Kumar *et al.* 2005). To fulfil 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. Present study would help in understanding the heterogeneous traffic flow conditions and will provide the basis for implementation of such system for four lane divided national highway networks.

Conclusions

1. In the present paper, a basic neural network based system for short term prediction of traffic volume for heterogeneous condition has been presented.
2. To evaluate model performance coefficient of correlation, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), standard deviation and χ^2 -test have been used.
3. Results of the study show that ANN model was able to predict vehicle count accurately even if vehicles category and their corresponding speeds were considered separately. It is obvious from the results that ANN can be applied successfully for short term traffic flow prediction with mixed traffic scenario in Indian context.

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Table 7. Summary of output from ANN modelling for testing stage

Correlation coefficient	Root Mean Square Error	Mean Absolute Error	Standard deviation	$\chi^2_{Calculated}$	$\chi^2_{Tabulated}$
0.9988	0.8586	0.6281	0.8573	4.1232	145.461

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