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PREDICTION OF BUS TRAVEL TIME USING ARTIFICIAL NEURAL NETWORK

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Abstract: The objective of this study is to apply artificial neural network (ANN) for development of bus travel time prediction model. The bus travel time prediction model was developed to give real time bus arrival information to the passenger and transit agencies for applying proactive strategies. For development of ANN model, dwell time, delays and distance between the bus stops was taken as input data. Arrivals/departure times, delays, average speed between the bus stop and distance between the bus stops were collected for two urban routes in Delhi. Model was developed, validated and tested using GPS (Global Positioning System) data collected from field study. Comparative study reveals that ANN model outperformed the regression model in terms of accuracy and robustness.

Keywords: travel time, artificial neural network, regression model, buses, prediction.

1. Introduction

In metropolitan cities like Delhi, traffic congestion is the major problem encountered in our daily life which leads to decrease in accessibility and reliability. These problems are due to the growth of vehicles specially the private and intermediate transport service (Sinha, 2003; TRB, 2001; ECMT, 2002). Apart from metro rail, bus transit also plays a key role in urban transportation system in Delhi. Therefore, it is necessary to improve the quality of bus transit system.

The bus transport system in Delhi can be enhanced by providing the real time bus arrival information to the passenger through Advanced Public Transport System (APTS) (Gurmu and Fan, 2104). The availability of timely and accurate information of bus travel time is significant, as it attracts more commuters and increases their satisfaction (Jeong and Rilett, 2004). Therefore, to provide passenger with this type of information there is an urgent need to develop travel time prediction model with sufficient accuracy.

In this study an attempt has been made to develop a travel time prediction model for urban bus route in Delhi, India with the help of artificial neural network. Travel Time is an important component of transport system because it affects the efficiency of system and service attractiveness. If a travel time is appropriate it attracts more commuters along the route and increases the commuters' satisfaction. Travel time between any two stops *i* and *i+1* for a journey *j* is defined as difference between the arrival time at stop *i+1* and departure time at stop *i* as shown in Eq. (1).

$$T_{i-i+1} = T_{Ai+1} - T_{Di} \tag{1}$$

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Where,

$T_{i\text{-}i+1}$ = travel between stop *i* and stop *i+1* for journey *j*

T_{Ai+1} = bus arrival time at stop *i+1*

T_{Di} = bus departure time

Organization of the paper is as follows: Section 2 covers the brief summary of past studies. Section 3 discuss about data collected through field studies. Section 4 provides the detail description of ANN. In Section 5 discuss the results for neural network training, validation and testing and also compare the ANN model results with regression model. In section 6 conclude with model discussion and recommending direction for future work.

2. Research Survey

Accurate prediction of bus travel time is important because it improves the quality of bus services. Accurate travel time information is essential as it attracts more commuters and increases commuter's satisfaction (Jeong and Rilett, 2004). A variety of prediction model has been developed in the past by various authors to predict bus travel time. The extensively used travel time prediction models were historical based models, regression models, kalman filter- based models, and artificial neural network models.

1. Historical Based Model: (Lin and Zeng, 1999; Williams and Hoel, 2003; Rice and Zwet, 2004). This type of model give the current and future travel time using historical travel time of prior journey based on the assumption that the traffic conditions remain stationary. Lin and Zeng (1999) developed arrival time estimation algorithms based on historical data to provide real time information. The algorithms were developed with different assumption on input data, like schedule adherence, waiting time at time-check stop, bus location data and schedule information. They developed the algorithms for buses in rural area without considering the effect of traffic congestion and dwell time at bus stop. The performance of four algorithms was evaluated in terms of accuracy, steadiness and robustness, and at last the result shows that four algorithms show best performance.

2. Regression Models: (Abdelfattah and Khan, 1998; You and Kim, 2000; Zhang and Rice, 2003; Patnaik et al., 2004; Ramakrishna et al., 2006; Yu et al., 2011; Chang et al., 2010). Regression model estimates the values of dependent variables from the values of independent variables. Regression model can work under unstable traffic condition. Advantage of regression models is that they tell which inputs are less or more important for predicting travel time. Abdelfattah and Khan (1998) build a linear and nonlinear regression model to predict bus delay using simulation data. The model was used to predict bus delay under normal condition, when one traffic lane is blocked. It meets the calibration test and was confirmed by field data. Patnaik et al. (2004) build a regression model to calculate arrival time of the bus and also identify the problem that occurred during processing of data collected through APC (Automatic Passenger Counting) units. The independent variables used were distance between

the stops, number of bus stops, number of passenger boarding and alighting, weather descriptor and dwell times. The model was used to calculate arrival time of bus under various conditions. They also identified that weather was an unimportant parameter in their model. Ramakrishna et al. (2006) builds a multiple linear regression model to predict bus travel time using GPS data. They also indentify that the parameters dwell stop at bus stops and intersection delay were very less correlated hence they were not considered for model development.

3. Kalman Filtering Models: (Chen and Chien, 2002; Cathey and Dailey, 2003; Chien and Kuchipudi, 2003; Shalaby and Farhan, 2004; Vanajakshi et al., 2008; Yu et al., 2010; Liu et al., 2012; Mazloumi et al., 2012; Jang, 2013; Gurmu and Fan, 2014). Kalman Filter is a recursive procedure that uses linear quadratic estimation model to estimates the future states of system. Shalaby and Farhan (2004) build a prediction model for bus arrival and departure time using Kalman filtering technique. The data was collected for 5 weekdays in the month of May with four buses which are equipped with GPS and APC (Automatic Passenger Counter).The Kalman filter technique is used for filter component and two algorithms were proposed for predictor component. Two Kalman filter algorithm was developed to estimate the running time and dwell time separately. Model was developed using four days of data, and validated using one day data. Hold out data and data from micro-simulation software VISSIM was used to check the performance of the proposed prediction model. The proposed model out performed than the other models (historical models, regression models and time lag recurrent neural models) in terms of accuracy.

4. Artifical Neural Network Models: (Smith and Demetsky, 1995; Dia, 2001; Chien et al., 2002; Tong and Hung, 2002; Mahmoudabadi, 2010; Zheng and Zuylen, 2013; Li and Chen, 2013). ANN model is used for solving non-linear complex data related problem. The implementation of ANN model is done in two phases: learning phase and recalling phase. In the learning phase the model is trained and weights are assigned and the recalling phase used to apply the weights assigned during learning phase. Smith and Demetsky (1995) build a back–propagation model using neural network-based technique to predict traffic volumes for intelligent vehicle highway systems. Chien et al. (2002) build a model using artificial neural network technique to predict the dynamic arrival time of bus. An adjustment factor was also developed to change predicted travel time with new input of real time data. CORSIM was used to simulate the data including volume and passenger demand. Finally, the reliability analysis for the proposed ANN will be evaluated by comparing the predicted and simulated arrival time at each stop.

3. Data Collection

The routes chosen for this study was bus route numbers 832 and 817 in Delhi, India. These routes were chosen to develop the travel time prediction model. These routes were chosen because these routes give direct connectivity to commercial and residential area to most of the commuters. The detail of both the routes are shown in Table 1.The urban bus route 832 runs from Janakpuri D Block to Inderlock Metro Station via Sagarpur, Tilak Nagar, Moti Nagar and Inderlock while route number 817 runs from Kair Village to Inderlock Metro Station via kair Depot, Tuda Mandi, KakrolaMor, Janakpuri East Bus Stop, Tilak Nagar, Inderlock as shown in Fig. 1.

Table 1

Detail of Urban Bus Route Number 832 and 817

S. No	*Detail of Bus Route*	*Name of Urban Bus Route*	
		Route No. 832	*Route No. 817*
1.	Length	14 (km)	28 (km)
2.	Travel Time	60-80 minutes	100-120 minutes
3.	Number of Bus Stops	33	53
4.	Number of Intersection	16	20

Data has been collected through site visit for the duration of 5 weekdays in the month of February, 2014. The data was collected separately for each route. For this study parameters were collected using handled GPS (Global Positioning System). Data collected include arrival time/departure times, delays, average speed between the bus stops and distance between the stops. Arrival /departure times at each stops was used to calculate the dwell time at each stop. Dwell time is an important component of travel time because it affects the quality of transit service. Dwell time at any stop *i* for a journey *j* is defined as difference between the departure time at stop *i* and arrival time at stop *i* as shown in Eq. (2).

$$DT_i = T_{Di} - T_{Ai} \tag{2}$$

Where,

DT_i = bus dwell time at stop *i*

T_{Ai} = bus arrival time at stop *i*

T_{Di} = bus departure time at stop *i*

The correlation among the variables has been shown in the Table 2. From Table 2 we found that speed is correlated with distance (0.55) and delay (0.597) and hence it was dropped. Therefore, the input variables considered to develop the model were dwell time, delays and distance between the stops.

Table 2

Correlation of Variables

Variable	*Dwell Time*	*Distance*	*Delay*	*Speed*
Dwell Time	1			
Distance	0.1813837	1		
Delay	-0.023431	-0.16655	1	
Speed	0.0428633	0.553016	0.597309925	1

4. Development of Model

4.1. Regression for Travel Time Prediction

To develop the travel time prediction model, a multi-linear regression analysis was performed on the data collected for two urban bus routes. The independent variables used in the model include distance between the stops, delays (at intersection and due to congestion) and dwell time at stops. The dependent variable used is Travel Time (TT in seconds). Regression models were developed with similar data set that was used to develop ANN model. In regression analysis the total data set has been divided in the two parts that is training and testing in the ratio 75 and 25 percent respectively. After the model is developed 25 percent data was used to test the developed model. The finally calibrated model is as shown in Eq. (3).

$$TT = a + b^{*}Distance + c^{*}Delay + d^{*}Dwell\ Time \quad (3)$$

Where, *a*, *b*, *c*, *d* are constants.

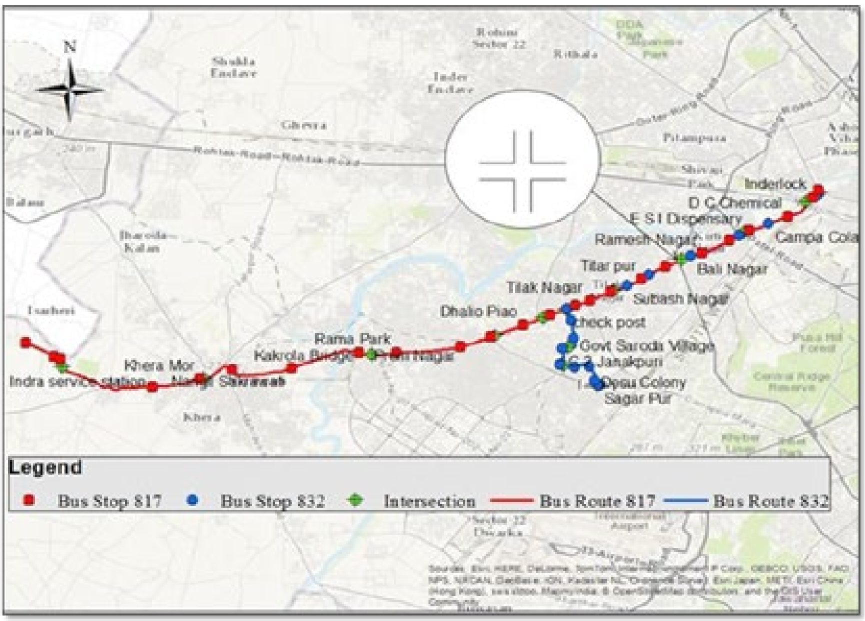


Fig. 1.
Layout of Bus Route No. 832 and 817

4.2. ANN for Travel Time Prediction

4.2.1. Basic Background

ANN is an information processing devices, which is comprised of large number of highly interconnected processing elements (PEs) that is inspired by the way biological nervous systems, such as brain process information (Hecht-Nielsen, 1987). In this information processing system, the elements are called neurons which process the information. The neuron with n inputs calculates its output as shown in Eq. (4) (Demuth, 2007).

$$a = f\ (\sum_{i=1}^{n} w_i\, p_i + b) \tag{4}$$

Where,

p_i is the value of i^{th} input

w_i is the value of i^{th} weight

b is the bias and f is an activation function of the neuron

Various types of transfer functions are available that is step, logistic and hyperbolic tangent (tanh) function. The arrangement of neurons in to layers and patterns of connection within and in-between layer are generally called as architecture of net. Fig. 2 shows the architecture of ANN model. Architecture of ANN includes an input layer, a hidden layer and an output layer. In the input layer, the number of PEs is the same as the number of input variables that are used to forecast the required output. In output layer, the PEs determines the variables to be forecasted. The connection between the input and output layers are depending on the complexity of the problem one or several intermediate layers of PEs, generally called hidden layers. Depending on the complexity of the problem the number of hidden PEs within these layers is decided by trial and error approach.

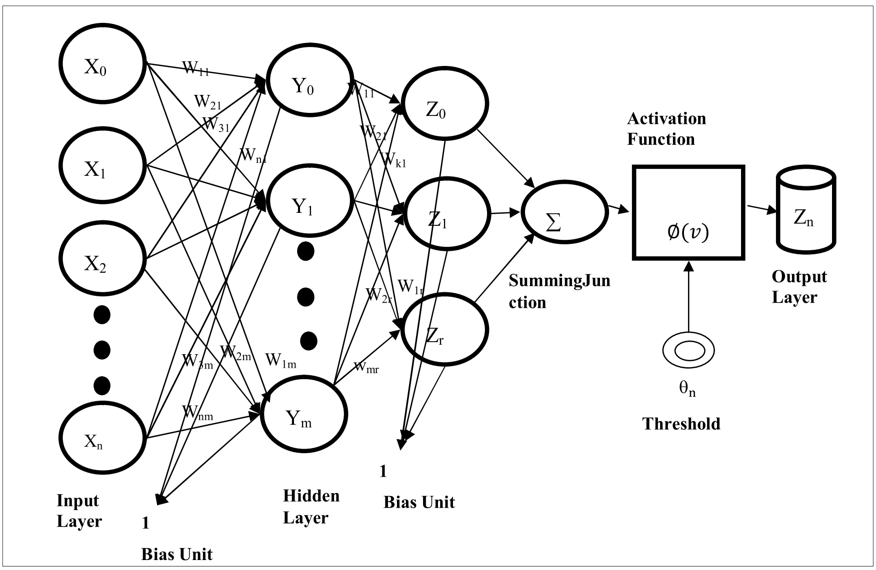


Fig. 2.
Structure of ANN

Depending upon the connections between PEs of different layers, various type network architectures are obtained. The processing elements are connected to each other by direct communication links, which is associated with weights. By adopting the weights of the communication links the ANN is supposed to learn correlation between input and output. To perform the training process large number of algorithms has been developed (Neural Ware, 1993). In this study the frequently used "backpropagation" network was implemented.

The training algorithm of back-propagation neural network involves four stages (Sivanandam et al., 2010):

1. Initialization of weight,
2. Feed Forward,
3. Back-propagation of error signals,
4. Updation of the weights and biases.

At firsts stage that is initialization of weights is used to initialize the weights to small random values. At second stage that is feed forward, each input unit receives an input signal and transmit it to output unit through hidden unit. If the output unit does not produce the desired output then third stage of back propagation of error signal is used in which error is propagated back to all the units in the previous layer. At the last stage, the weights and biases are updated in accordance with error signal. With these steps performing iteratively, the error can be minimized between network output and desired output using a predefined learning rule (Sivanandam et al., 2010).The transfer functions (i.e. activation function) are needed to establish nonlinearity into the network. For back-propagation, learning transfer function must be differentiable and bounded. The development procedure is completed once the network is trained.

The algorithm works best when the network inputs and outputs are normalized roughly in the range [-1, 1] (Demuth et al., 2007). For normalizing the input and output values according to the range Eq. (5) was used as shown below:

$$X^s = 2(X - X_{min})/(X_{max} - X_{min}) - 1 \qquad (5)$$

Where X^s gives the normalised value, X is the original value, X_{min} and X_{max} are the minimum and maximum value of X.

4.2.2. Building Neural Network

ANN has been applied for a wide variety of transportation problems and is relatively easy to use. Neural network automatically discover the relationship between the variables and naturally the fitting take place. Generally the network architecture is the single place where intuition of researchers comes into play. In ANN modelling based on the problem once can choose the required number of variables as there is no limit on the number of variable. ANN provides flexibility, massive parallelism, learning and generalization ability, accuracy and some amount of fault tolerance in prediction of travel time. For design of neural network there is no general theory or method. Mostly trial and error approach is used. During design of neural network the complexity arises while modelling of non-linear problem. Architecture of network, number of input variables, choosing of training algorithm and activation function are the basic features which must be considered in the design of neural network. All these are problem dependent quantities.

A set of data records considered for analysis of models are shown in Table 3. Whole database has been divided in to three parts training, validation and testing in the ratio 65, 15 and 25 percentage respectively. In this study Model III was trained nine times using same set of training data (614 data records) and different number of neurons. Similarly, the model VI was trained nine times using same set of training data (979 data records) and different number of neurons. Dwell time, delays and distance between the stops were considered for development of models. Validation and testing data was used to compare the performance of ANN models. The performance measures MSE (Mean Square Error) and coefficient of correlation (R^2) were used to estimate the prediction results. Table 4 and Table 5 give the detail of network with different structure for Model III and Model IV. From Table 4 and Table 5 it was found that network structure (3, 5, 1) and (3, 15, 1) produces best prediction.

Table 3

Data Records Considered for Analysis of Models

S. No	*Models Name*	*Data used for Development of Models*	*Set of Data Records*
1.	Model I	832 (upstream)	512
2.	Model II	832 (downstream)	512
3.	Model III	832 (combined upstream and downstream)	1024
4.	Model IV	817 (upstream)	832
5.	Model V	817 (downstream)	800
6.	Model VI	817 (combined upstream and downstream)	1632

Table 4

Detail of Network with Different Structure for Model III

Trial No	*Train 1*	*Train 2*	*Train 3*	*Train 4*	*Train 5*	*Train 6*	*Train 7*	*Train 8*	*Train 9*
No. of hidden layers	1	1	1	1	1	1	1	1	1
No. of hidden neurons	3	4	5	6	7	9	11	12	15
Training Function	Trainlm	Trainlm	Trainlm	Trainlm	Trainlm	Trainlm	Trainlm	Trainlm	Trainlm
Transfer Function	Tansig	Tansig	Tansig	Tansig	Tansig	Tansig	Tansig	Tansig	Tansig
Number of epochs	1000	1000	1000	1000	1000	1000	1000	1000	1000
MSE (T)	5.30E-2	4.85-2	4.09E-2	4.83E-2	4.96E-2	4.83E-2	5.67E-2	4.95E-2	4.91E-2
MSE (V)	5.83E-2	5.73E-2	4.61E-2	5.84E-2	5.96E-2	6.31E-2	5.37E-2	4.77E-2	5.41E-2
MSE (Y)	5.56E-2	5.48E-2	4.24E-2	5.75E-2	5.38E-2	5.58E-2	5.93E-2	5.66E-2	6.34E-2
R(Y)	0.8309	0.8480	0.8612	0.8458	0.8219	0.8505	0.8400	0.8521	0.8362

T = Training phase, V = Validation Phase, Y = Testing Phase

Table 5

Detail of Network with Different Structure for Model VI

Trial No	*Train 1*	*Train 2*	*Train 3*	*Train 4*	*Train 5*	*Train 6*	*Train 7*	*Train 8*	*Train 9*
No. of hidden layers	1	1	1	1	1	1	1	1	1
No. of hidden neurons	3	4	5	6	7	9	11	12	15
Training Function	Trainlm	Trainlm	Trainlm	Trainlm	Trainlm	Trainlm	Trainlm	Trainlm	Trainlm
Transfer Function	Tansig	Tansig	Tansig	Tansig	Tansig	Tansig	Tansig	Tansig	Tansig
Number of epochs	1000	1000	1000	1000	1000	1000	1000	1000	1000
MSE (T)	2.62E-3	3.43E-3	2.07E-3	2.19E-3	2.27E-3	2.79E-3	1.83E-3	2.02E-3	1.92E-3
MSE (V)	1.56E-3	4.92E-3	2.63E-3	2.42E-3	2.56E-3	1.78E-3	2.09E-3	1.08E-3	2.12E-3
MSE (Y)	7.34E-3	3.05E-3	3.09E-3	3.03E-3	1.95E-3	3.55E-3	5.28E-3	4.50E-3	2.09E-3
R(Y)	0.9219	0.9232	0.9329	0.9251	0.9330	0.9349	0.9042	0.9065	0.9357

After the number of hidden neurons that produces best prediction for Model III and Model VI has been found. Then, Model I and Model II was trained using 307 set of training data and five numbers of hidden neurons (that produces best prediction for Model III). Similarly, the Model IV and Model V was trained using 499 and 480 set of training data and fifteen number of hidden neurons (that produces best prediction for Model VI).

The detail of the network structure for all the six models has been illustrated in Table 6. Based on the performance measure that is MSE and R^2 it was found that Model I and Model II gives best prediction than Model III. Similarly, Model IV and Model V give best prediction than Model VI. Thus, it was found the separate model for route upstream and downstream gives best prediction that combined model. This was due to large number of disturbance in the combined model.

Table 6

Detail of Network Structure for all Six Models

Model Name	*No. of hidden layers*	*No. of hidden neurons*	*Training Function*	*Transfer Function*	*Number of epochs*	*MSE (T)*	*MSE (V)*	*MSE (Y)*	*R(Y)*
Model I	1	5	Trainlm	Tansig	1000	1.85E-2	2.29E-2	2.09E-2	0.9290
Model II	1	5	Trainlm	Tansig	1000	6.34E-3	5.45E-2	7.59E-3	0.9612
Model III	1	5	Trainlm	Tansig	1000	4.09E-2	4.61E-2	4.24E-2	0.8612
Model IV	1	15	Trainlm	Tansig	1000	2.03E-4	1.78E-3	1.87E-3	0.9616
Model V	1	15	Trainlm	Tansig	1000	9.12E-4	1.52E-3	1.81E-3	0.9713
Model VI	1	15	Trainlm	Tansig	1000	1.92E-3	2.12E-3	2.09E-3	0.9357

5. Results and Discussion

Fig. 3 shows the graph between the Actual and Predicted travel time of four models for testing phase. The actual and predicted travel time was compared to check the validity of ANN models. Fig. 4 shows the scatter plots for models validation.

The performances of the developed models were evaluated by applying paired t-test. The paired t-test values of the models at 5% level of significance are shown in the Table 7. Since the calculated t-value is less than the tabulated t-value for the models developed separately for each route, therefore using null hypothesis it was concluded that here was no major variation among the actual and predicted values. Hence, the models developed separately for each route are more suitable.

In this study, the result of the developed ANN models was compare with multiple regression models to check the accuracy and robustness of the models developed separately for each route. Three measure of effectiveness were calculated for all the four models: (1) RMSE (Root Mean Square Error) (2) MAPE (Mean Absolute Percentage Error) (3) R^2 (coefficient of correlation). RMSE is defined as the difference between the predicted and actual travel time. MAPE is defined as the average difference between the predicted and actual travel time. MAPE and RMSE have been defined as shown in the Eq. (6) and (7).

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left| \frac{y_1 - y_0}{y_0} \right| \times 100\,\% \tag{6}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_1 - y_0)^2} \tag{7}$$

Where,

y_1 = is the predicted values of transit travel time

y_0 = is actual values of transit travel time

n = is the number of data point in the set

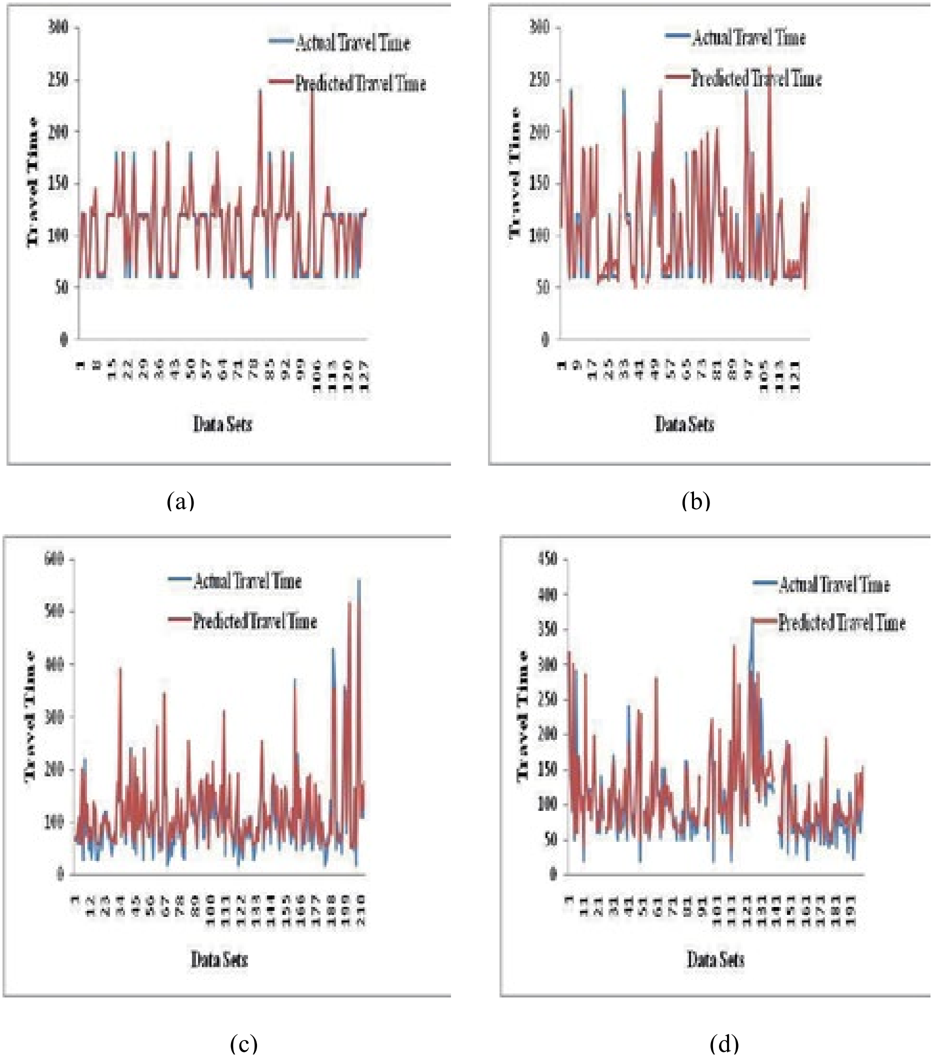
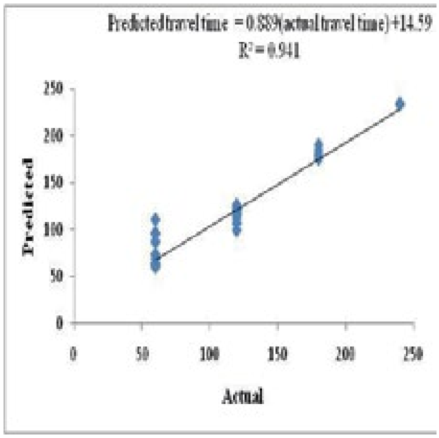
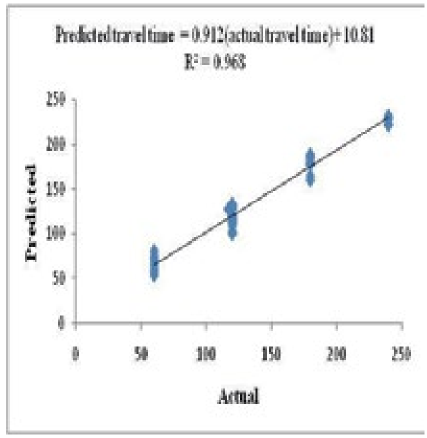


Fig. 3.
Actual and Predicted Travel Time of Four Models for Testing Phase
(a) Model I (b) Model II (c) Model IV (d) Model V



(a)



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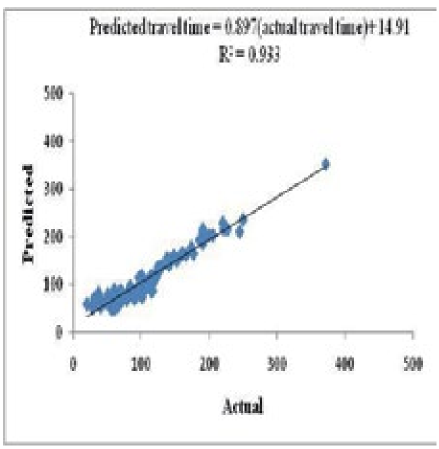
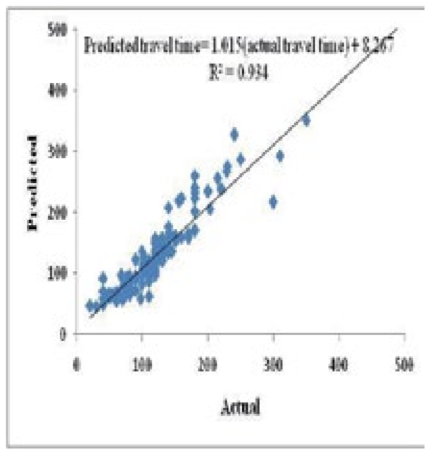


(c)



(d)

Fig. 4.
Scatter Plot between Actual and Predicted Travel Time of Four Models for Validation Phase (a) Model I (b) Model II (c) Model IV (d) Model V

Three measure of effectiveness that is RMSE, MAPE and R^2 for regression and ANN models are shown in the Table 8. Results in the Table 8 shows that ANN models depict greater accuracy and robustness with less error as compared to regression models.

During training process ANN learns from examples and thus weights are adjusted accordingly to use this information during testing and cross validation. As compared to analytical and statistical model, ANN model generally produce better results with minimization of errors. Apart from good results and less error as compared to regression model, still there are some problems related to ANN modelling. In ANN modelling it is not possible to find the effect of each individual variable independently.

Bus travel time depends on multiple factors such as distance between stops, dwell time, delays, speed, arrival/departure time and schedule adherence. All these factors make travel time modelling a difficult and non linear problem. In a particular case study it is not possible to consider all the factors because of technical problem related with data collection. In this study, schedule adherence has not been taken into consideration.

Table 7

Summary of Output of Four Models for Testing Phase

Models Name	*R2*	*RMSE*	*MAPE*	*Standard Deviation*	*t-test calculated*	*t-test tabulated*	*DOF*
Model I	0.9290	10.432	6.527	10.268	-2.263	1.9788	127
Model II	0.9612	13.233	10.552	13.007	-2.341	1.9788	127
Model IV	0.9616	26.368	24.423	24.592	-5.147	1.9719	207
Model V	0.9713	32.830	20.573	32.721	-1.527	1.9720	199

RMSE = Root Mean Square Error, MAPE = Mean Absolute Percentage Error, DOF = Degree Of Freedom

Table 8

Comparison between Regression and ANN Model for Testing Phase

Model Name		*Equation*	*R2*	*RMSE*	*MAPE*	*Standard Deviation*
Regression	Model I	0.937x+11.42	0.812	18.427	16.234	17.874
	Model II	0.974x+8.545	0.889	23.51	18.940	22.876
	Model IV	1.059x+0.588	0.862	34.750	25.193	34.041
	Model V	1.121x-12.96	0.881	46.692	22.054	46.743
ANN	Model I	0.914X+11.17	0.9290	10.432	6.527	10.268
	Model II	0.954x+7.678	0.9612	13.233	10.552	13.007
	Model IV	0.952x+7.767	0.9616	26.368	24.423	24.592
	Model V	0.962x+6.876	0.9713	32.830	20.573	32.721

6. Conclusion

In the present study, ANN model has been developed to predict bus travel time for two selected urban bus route in Delhi. The performance of the model is evaluated using coefficient of correlation (R^2), root mean square error (RMSE), mean absolute percentage error (MAPE), standard deviation and t-test. Results shows that ANN model gives better results than regression model. For further work it is suggested that prediction model can be improved by incorporating the information of schedule adherence. It is also suggested to use Kalman Filter algorithm to predict travel time and compare the results with ANN model.

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