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Transportation Research Procedia 17 (2016) 263 – 272

Transportation Research Procedia

www.elsevier.com/locate/procedia

11th Transportation Planning and Implementation Methodologies for Developing Countries, TPMDC 2014, 10-12 December 2014, Mumbai, India

Prediction of Bus Travel Time using ANN: A Case Study in Delhi

Johar Amita [a*], Jain S.S. [b] and Garg P.K [c]

[a]Ph.D.Research Scholar, Centre for Transportation System (CTRANS), IIT Roorkee, Roorkee 247667, Uttarakhand, India,

[b]Professor, Transportation Engineering Group, Department of Civil Engineering & Associate Faculty CTRANS, IIT Roorkee, Roorkee–247667, Uttarakhand, India

[C] Professor, Geomatics Engineering Group, Department of Civil Engineering & Associate Faculty CTRANS, IIT Roorkee, Roorkee-247667, Uttarakhand, India

Abstract

Quality of the bus travel time is improved by the accurate prediction of bus travel time. Accurate travel time information is essential as it attract more commuters and increase commuter's satisfaction. The prime objective of this study is to develop a model that predicts bus travel time based on (Global Positioning System) GPS data using artificial neural network (ANN). The bus travel time prediction model developed in this study includes the number of passengers boarding and alighting, average nonstop trip time, and number of dwells at each at each stop. The real world data collected from route no 832 of Delhi Transport Cooperation (DTC) was used to developed and validate the model. The performance of the developed model is estimated by comparing it with other model using conventional measures such as mean absolute error and root mean square error. Finally, the result indicates that developed model is slightly proficient in achieving predicted travel time with sufficient accuracy.

Peer-review under responsibility of the Department of Civil Engineering, Indian Institute of Technology Bombay

Keywords: ANN,GPS,Prediction,Bus, Travel Time;

* Corresponding author. Tel.: +917895168717.
E-mail address: avamitamita@gmail.com

Peer-review under responsibility of the Department of Civil Engineering, Indian Institute of Technology Bombay
doi:10.1016/j.trpro.2016.11.091

1. Introduction

Accurate prediction of travel time for the bus is significant for both the operators and users. Through the actual travel time the transit operators can easily indentify the unpredicted service interruptions and delays at bus stop and can take managerial and practical actions, such as training of operator and adjusting schedules for improved performance (Sun et al 2007). Actual travel time can also be informed to passengers through various medium like electronic board displayed at the bus stops (Schweiger 2003). Hence, the quality of the bus service is improved, which makes public transport system efficient and user-friendly as compared to other transport modes.

Accurate travel time information plays an important role in reducing passengers waiting time (Xinghao et al 2013) and due to this the passengers can arrive at the bus stops closer to the schedule time. This type of improved information will attract even those commuters who are using intermediate public transport and private vehicles

2. Literature Review

In the previous years, various studies have been conducted that use artificial neural network in predicting the transit travel time. Chien *et al.* (2002) build an ANN model to predict 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.

Shalaby and Farhan (2004) build a bus arrival and departure time prediction model using kalman filter algorithm. The data used for developing the model was collected through AVL (Automatic Vehicle Locator) and APC (Automatic Passenger Counter). The performance of the model was tested on real world data and data obtained from microsimulation model using error indices such as mean relative error, root square relative error and maximum relative error. Finally, the result indicate that kalman-filter model perform better than other traditional model in terms of efficiency**.**

Jeong and Rilett (2004) build an ANN model to estimate arrival time of bus using data collected through automatic vehicle location (AVL). Inputs used in the model were service time at every stop and traffic congestion. Formulations of different model were used like historical model, regression model and artificial neural network. The model demonstrated its superior performance by comparing with other model in terms of mean absolute percentage error (MAPE).

Patnaik *et al.* (2004) used regression model to calculate arrival time of the bus. Automatic passenger counters placed on the buses was used to collect the data. Lastly, the developed model could be used to calculate arrival time of bus at various conditions. Finally, results identified that the proposed models estimate bus arrival times under various situations.

Myung *et al*. (2010) build a prediction model by combining vehicle detector system (VDS) and automatic tool collection system (ATC) data using k-nearest method. They also set up the criteria for traffic condition that directly used the data acquired through ATC without going through prediction process. The developed model was compared with other model to check the efficiency. They also stated that proposed model is more accurate as it does not require long training programs and it is easily transferable.

Zhang and Teng (2013) developed a dwell time model that includes number of passengers boarding and alighting and other secondary factors, like crowding and fare type. Model was validated with the data of bus line Jiading 3 in Shanghai, China. Finally, comparing the model with the previously developed model for the same route indicates that model can be well applied to the high demanded urban bus lines, especially in the presence of high occupancy of vehicles.

3. Objective and Scope

The major purpose of this study was to develop a bus travel time prediction model based on GPS data using ANN techniques. The predicted travel time helps commuters in making their trip decision. The real world data collected from route no. 832 was used to develop and validate the data. The model was developed using parameters like number of passengers boarding and alighting, average nonstop trip time and number of dwells at each stop. The performance of the ANN model is evaluated by comparing the conventional measures such as the Mean Absolute Percentage Error (MAPE) and Root Mean Square Error (RMSE) with LRM (Linear Regression Model).

4. Data Collection

Data for the present study was collected from the route number 832 in Delhi from Janakpuri D Block to Jai Mata Market as shown in Fig. 1.The route is about 17.4 km in length, having 43 bus stops. Data was collected by boarding a DTC bus from origin of a route under study to its destination and vice- versa. This was conducted for 6 days (20 to 25) in the month of October 2013, for the route at different times of the day; specially, peak period (i.e., morning and evening) and off-peak periods (i.e., after noon). In this work, arrival time, departure time and dwell time was collected using handled GPS and alighting and boarding of passenger collected manually because automatic passenger counter (APC) was not available. The frequency of buses for week days during peak period was 30 minutes and off-peak period was 60 minutes. A total of 40 trips data was collected, out of which 20 trips were collected for peak period and 20 trips were collected for off-peak period. The data was collected for those buses which go to jai mata market excluding the buses that terminate at inderlock metro station. The model was developed separately for both peak and off-peak data and analysis of variance (ANOVA) test was done but there was no significant variation observed between results for the peak and off-peak travel time as p-value > 0.05 as shown in Table 1. Therefore, peak and off-peak data were combined together for model development and validation.

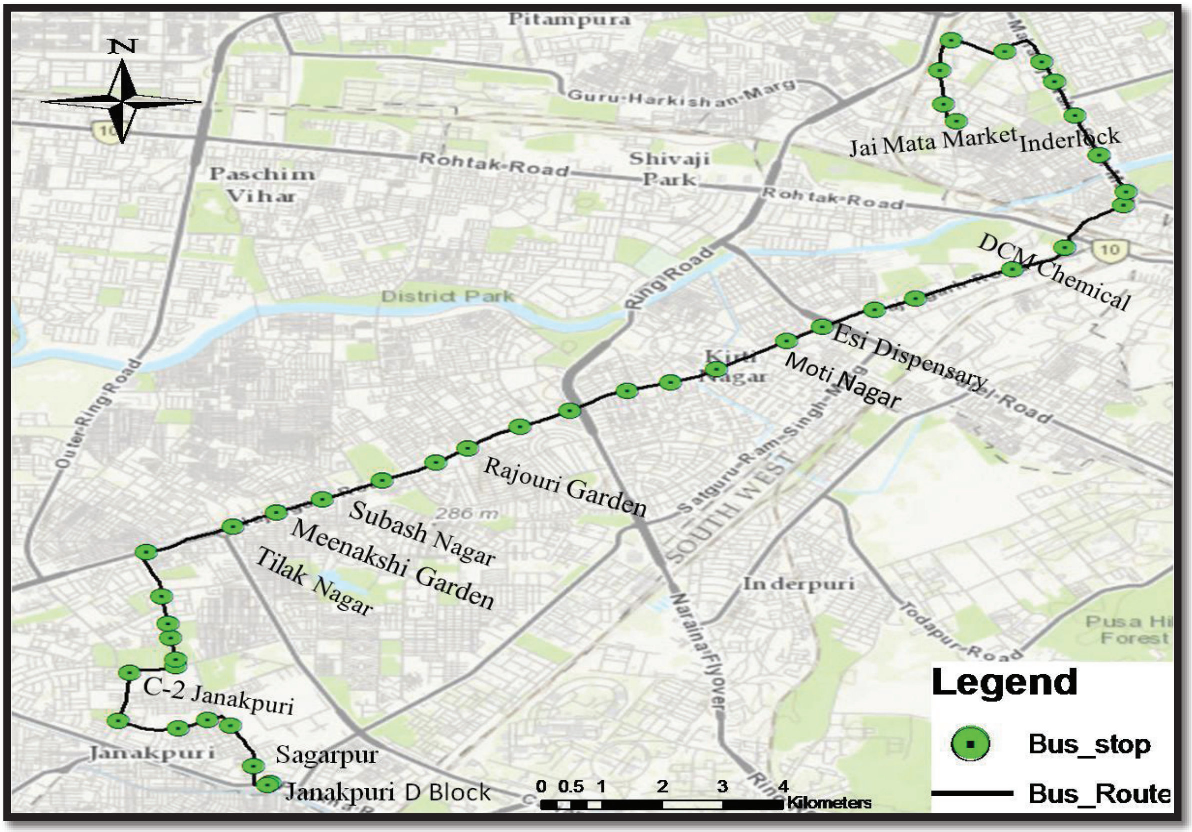

Fig. 1 Layout of Bus Route 832 in Delhi

Table 1. Anova Test for Peak and OffPeak Travel Time

Groups	Count	Sum	Average	Variance		
Peak Travel Time	20	82500	4125	129552.63		
Offpeak Travel time	20	79980	3999	554125.26		
ANOVA						
Source of Variation	SS	df	MS	F	P-value	F crit
Between Groups	158760	1	158760	0.464	0.499	4.09
Within Groups	12989880	38	341838.94			
Total	13148640	39				

5. Development and Validation of Model

5.1. Linear Regression Model (LRM)

Regression analysis was done to develop a predicted travel time model for chosen bus route in Delhi. The predicted travel time model began with the departure time from the first stop and ended with the arrival time at the last stop, excluding the layover time at both ends (Bertini and EI-Geneidy 2004). As observed by the panel Ts was taken as dependent variable and average non-stop trip time(T_o), number of dwells (N_d), number of passenger boarding (N_b) and number of passenger alighting(N_a), have been taken as independent variables. The model was developed after analyzing the correlation coefficient of all the three independent variables, which was less than 0.5. Out of 40 trips, 28 trips (1148 data sets) were taken for development of model and 12 trips (492 data sets) for model validation. The proposed model for urban bus route has been presented by Eq. 1.

$$Ts = 3659.22+12.23\ N_d+0.73\ N_b+0.65N_a \tag{1}$$

Where Ts = transit travel time, N_d= number of dwells at each stop, N_b= Number of passenger boarding and N_a= number of passenger alighting

Above equation reveals that non-stop trip time is 3659.22 seconds, each stop adds 12.23 seconds to the trip (time taken for acceleration and de-acceleration of bus and opening and closing of door), each passenger boarding add 0.73 seconds and each alighting passenger add 0.65 seconds. This formula considers that the alighting and boarding of passengers take place from both the doors.

5.2. Artificial Neural Network (ANN)

Developing of ANN model includes choosing a problem domain, preparing topology of network, including number of units in each of input, output and hidden layers, learning parameters and tolerance levels, for training the network choose learning paradigm and evaluation of the trained network for unknown samples (shah *et al*. 2013). For the present study, input layer of ANN model includes the number of passenger boarding & alighting, number of times a bus stop in a trip and output layer was actual trip time of 40 trips as collected for the selected urban route. To predict travel time in ANN model the network developed was first trained and then checked with another set of data that was not considered for training. Training set is defined as the network that uses the inductive-learning principle to learn from a set of examples**.**

Total of 40 trips was used, out of which 28 trips (70%) were arbitrarily selected for model training and remaining 12 trips (30%) were considered for model testing. For fast training of network Levenberg–Marquardt back-propagation algorithm together with Bayesian regularization was chosen (Demuth et al 2007). The algorithm works best when the network inputs and targets are scaled roughly in the range [-1, 1] (Demuth et al 2007). For normalizing the input and output values according to the range Eq. 2 was used as shown below:

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

Where X^s = gives the scaled value of factors with maximum and minimum values of X_{max} and X_{min} respectively.

Hyperbolic tangent sigmoid transfer function was used as the activation function for hidden and output layers. For selection of training sets, training ANNs and initializing the values of weights and biases the MATLAB software was used. Table 2 and Table 3 show the weights and biases values of the trained networks.

Optimal ANN model was developed using different combinations of network architecture. The ANN (i,j,k) indicates a network architecture with i, j and k neurons in input, hidden and output layers, respectively. The architecture (3, 9, 1) appears to be best suitable topology. Fig. 2 and Fig. 3 represent the relationship between the Actual Travel Time (ATT) and Predicted Travel Time (PTT) values during training and testing of model.

Table 2. Weight of Trained Network

$w_{i,j}^k$	K	J								
i		1	2	3	4	5	6	7	8	9
	1	1.448	1.683	-1.751	1.56	1.031	-1.765	-1.410	0.4993	2.005
1	2	2.139	-1.42	2.209	1.725	-0.113	1.317	-2.279	-0.833	1.822
	3	1.344	1.905	0.731	-1.752	2.720	1.904	1.137	2.745	1.065
2	1	-0.156	0.225	-0.477	0.299	-0.680	-0.324	-0.659	-0.585	0.470

$w_{i,j}^k$ is the weight between j[th] neuron of i[th] layer and of k[th] neuron of previous layer

Table 3. Biases of Trained Network

B_i^j	J								
i	1	2	3	4	5	6	7	8	9
1	-2.912	-2.184	1.456	-0.728	0	-0.728	-1.456	2.184	2.912
2	0	-	-	-	-	-	-	-	-

B_i^j is the bias of j[th] neuron of i[th] layer

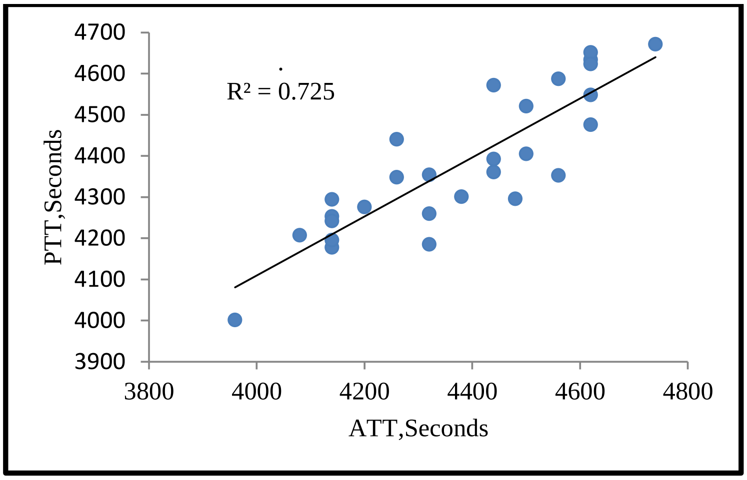

Fig. 2 ANN Result for Development of Ts Model

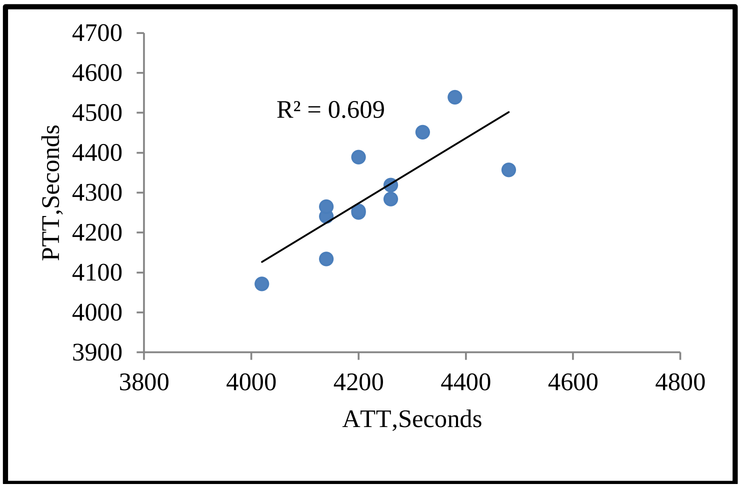

Fig. 3 ANN Result for Validation of Ts Model

The validity of the developed model is again tested using joint t-test. If the actual and observed data follow normal distribution then only the joint t-test is appropriate. Therefore, to test the goodness of fit on both the data set X^2- test was performed. In X^2 test two hypotheses were assumed as mentioned below.

Null hypotheses = Predicted data follows normal distribution

Alternative hypotheses = Predicted data does not follow normal distribution

$$\text{Chi} - \text{Square} = \frac{(O_F - T_F)^2}{T_F} \tag{3}$$

The value of Chi-square was calculated, null hypothesis is accepted if the calculated X^2 is less than tabulated X^2 value and vice-versa.

Where, O_F = Observed Frequency, T_F = Theoretical Frequency.

Table 4. Results of X^2Test on Datasets

X^2 Test	$X^2_{calculated}$	X^2_{tabled}	DOF	Significance level($\propto$)	Null Hypothesis (accepted/rejected)
For actual Travel Time Data	3.38	19.675	11	0.05	'Accepted'
For Predicted Travel Time Data	0.52	19.675	11	0.05	'Accepted'

DOF: Degree of Freedom

From Table 5, it was identified that the actual travel time and predicted travel time values follows normal distribution. Therefore, joint t-test is performed for validation of proposed model. Tables 4 give the results of joint t-test as given below.

Table 5. Paired t-test for Validation of Proposed Model.

Terms	Formula	Values
Sum of variation ($\sum z$)	(Actual-Predicted)	-817.674
Total no. of trips (n)	-	12
Average of (z)	$(\sum z)/n$	-68.140
Sum of square of difference	$\sum z^2$	132034.635
Square of sum of difference	$(\sum z)^2$	668591.330
	$(\sum z)^2 /n$	55715.944
$\sum d\, z^2$	$\sum z^2 - (\sum z)^2 /n$	76318.690
Variance((σ^2)	-	6938.063
Square root of variance	-	83.295
$t_{calculated}$	-	-0.818

As $t_{calculated}$ = -0.818 which is less than the $t_{tabulated}$ = 1.796 (df = 11 and α= 0.05). So, it was identified that there was no major variation among the observed and predicted travel time values at 95%, confidence level and thus the proposed travel time model was suitable.

6. Comparing the Models

Mean absolute percentage error and root mean square error is an applicable measure to compare the efficiency of the prediction models. Mean absolute percentage error and root mean square error has been defined as shown in Eq. 4 and Eq. 5. MAPE represents the average percentage difference between the actual and predicted travel time between the trips. The comparison between the actual and predicted travel time for 12 trips (data used for validation of model) and 28 trips (data used for development of model) is as shown in the Fig. 4 and 5. Fig. 4 and 5 shows that the error bars around the actual and predicted travel time values vary between ±5percent. Performance evaluation of both models has been calculated and the result is shown in the Table 6.

$$MAPE = \frac{1}{n}\sum_{i=1}^{n} \left| \frac{y_1 - y_0}{y_0} \right| \times 100\ \% \tag{4}$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_1 - y_0)^2} \tag{5}$$

Where

y_1 is the predicted/simulated values of transit trip time

y_0 is actual values of transit trip time

n is the number of data point in the set

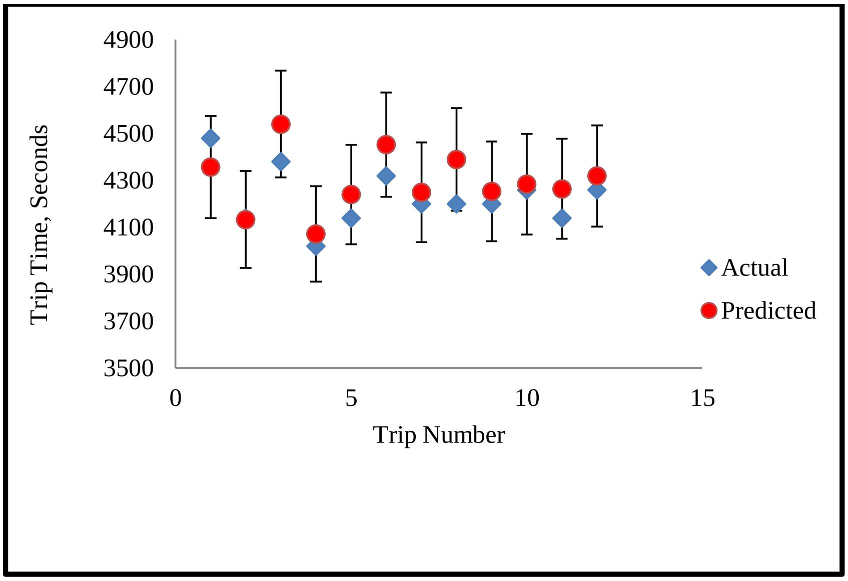

Fig. 4 Actual and Predicted Travel Time for Validation Data

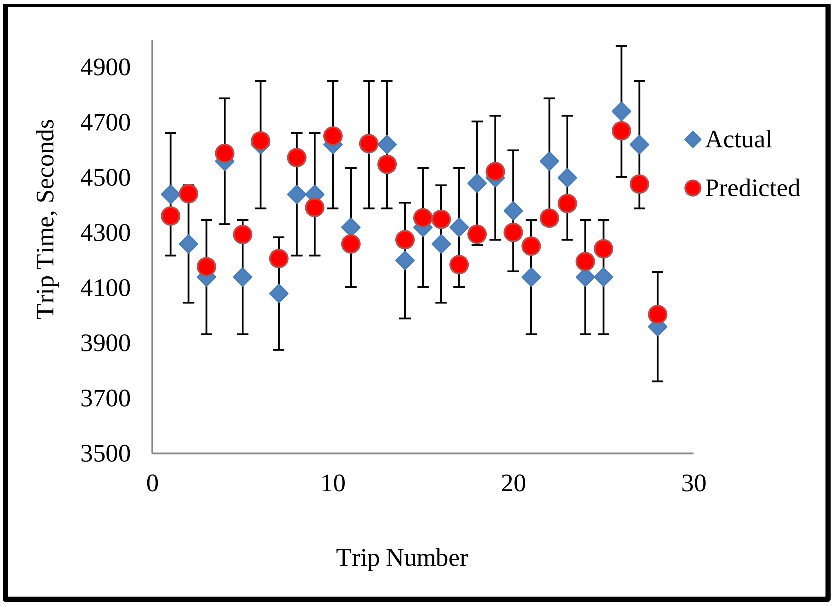

Fig. 5 Actual and Predicted Travel Time for Development Data

Table 6. Performance Evaluation of Models

S.No	Model	MAPE		RMSE	
		Training	Testing	Training	Testing
1.	Linear Regression Model (LRM)	2.31	2.31	118.21	107.54
2.	Artificial Neural Network (ANN)	**1.98**	**2.09**	**101.73**	**103.89**

Result in the Table 6 shows that ANN model yield slightly better prediction than LRM. This result can be improved if model is developed and validated with the data for considerably more trips.

7.0 Conclusion

Accurate prediction of arrival time is important as it attracts more commuters and increase commuter's satisfaction. In the present study, the proposed ANN model was used to predict bus travel time for the selected urban route. The total of 40 trips was used for analysis out of which 28 trips (i.e., 70 %) were used for model training and 12 trips (i.e., 30 %) were used for model testing.

Using χ^2 and joint t-test the proposed ANN model was validated. ANN model was examined using various trails. Model architecture (3, 9, 1) has been recommended by changing the number of neurons in each hidden layers and changing the number of hidden layers. The performance evaluation of ANN model was done by comparing with other model using conventional measures. Finally, the result shows that the developed model is efficient and giving results with sufficient accuracy. For Further work it is recommended that one month data should be collected for the selected route to get more steady results.

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