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Modeling of BRT System Travel Time Prediction Using AVL Data and ANN Approach

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Abstract

Improving the quality of public transportation systems and encouraging passengers to use them are effective solutions for reducing transportation problems in metropolitan. Prediction of travel time and providing information to passengers are significant factors in this process. In this research not only the travel time components in Bus Rapid Transit (BRT) system were investigated but also an Artificial Neural Network (ANN) model and a regression model for travel time prediction were presented. To enhance this aim, data was collected by AVL data and field observation and after investigating the primary independent variables, the significant ones were determined using statistical analysis, then ANN development was done. Moreover, linear regression method was used for this purpose. The results prove that although both models have high level of prediction accuracy, ANN model outperform the regression model and the accuracy for the route sections with no signalized intersections is higher than the others.

Keywords: Bus Rapid Transit (BRT), Travel Time Prediction, Artificial Neural Network (ANN), Linear Regression, Automatic Vehicle Location (AVL)

1. Introduction

In recent years, various methods have been proposed in order to solve the urban traffic problems. Improving public transportation system is one of the most important ones. The main policy of transit agencies is increasing the attractiveness of public transportation system with high mobility and accessibility to passengers in order to improve the quality

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of life (Gurmu, 2010; Kieu et al, 2012). Bus travel time prediction has the potential to participate significantly in the operations of providers and managers of public transport. On the other hand, bus travel time predictions can help public transport operators in the effective management by optimizing the program and understanding the reliability of their system (Higatani et al, 2009). Moreover, Bus travel time prediction can reduce anxiety and stress of passengers by helping them to select the bus routes with the minimum waiting time (Bates et al, 2001). Bus travel time prediction models can predict the arrival time of public transport vehicles at the stations. This information, particularly in the case of congestion, helps passengers in choice of transportation mode and route choice by providing more travel options (Kieu et al, 2012). Bus Rapid Transit (BRT) was known as a reliable system with high performance that transports fast, comfortable and economical. In addition, because of existence of dedicated lanes along routes, delay time would be decreased (Raju et al, 2020). Due to increasing BRT systems and many daily trips that can be done with these systems in the cities, presenting models or techniques for desirable prediction of travel time can have a determinant role in order to achieve the above objectives.

As travel time is defined in Transit Capacity and Quality of Service Manual, is the total time in which to travel from origin to destination (Kieu et al, 2012). In this study, the purpose of travel time is total travel time that is from one bus station to the next station, or in other words the arrival time difference of a bus at two consecutive stations which consists of two main components. Running time is the first component that is the time spent in the vehicle traveling from station to station, or it is defined as the difference between bus departure time at current station and bus arrival time at next station. The second part or the dwell time is defined as time spent in a vehicle stopped at a station or in other words, it is the time difference between the arrival and departure of buses in each station (FTA, 2009). Figure 1 shows the concept of travel time and dwell time at the station.

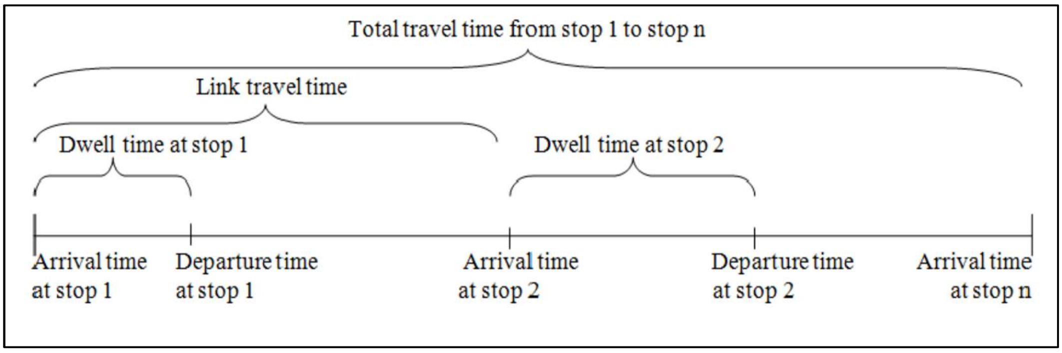

Figure 1: Definition of Travel Time and Dwell Time
Source：(Kieu et al. 2012).

2. Literature Review

Travel time plays an important role in choosing type of transportation system in order to save time and improve the efficiency of system (Mohammadi et al, 2018). The process of travel time prediction for bus transit systems have been studied by various researchers around the world and today various models have been introduced to predict this time. These models are classified in 6 groups of historical average models, time series models, regression models, Kalman filter models, artificial neural network models and support vector machine models (Gurmu, 2010).

An expected time of arrival (ETA) statistical model was developed for a school bus service. This model predicted arrival time from the input of two categories: the last several days' historical data and the current day's operational conditions. An operational strategy was additionally incorporated into the model to reduce the risk that an overestimated arrival time could result in missing the bus. Since the buses were utilized during stations and the fixed routes and on the basis of pre-release programs, they postulated that the travel time between the two stations can be explained by the historical data from the bus travel times. The authors examined the model using data collected from the actual operation of school buses. Automatic Vehicle Location (AVL) systems were installed on these buses. With operational strategy, this model was a reliable enough that about 99% -100% of the students did not miss the bus and its service was in an acceptable waiting time of 162-177 seconds (Chung et al, 2007).

Applying the multiple regression models, bus travel times in an urban network in Sydney were analyzed and variables that have a significant impact on changes in bus travel time (i.e. non-stop running time, the delay caused by the traffic lights, delay due to roundabouts and lost times at bus stops, which are useful for the classification of delays along a route) were identified and the percentage of time that buses spend in each stage of a trip were estimated. In this research the main objective was the consequences analysis of the strategy change of paying for a bus service. By using estimates of passenger boarding times with alternative fare payment methods (cash, magnetic strip, contactless card and off-board payment), operational speed and benefits of upgrading the fare payment technology can be calculated, including savings on fleet size requirements, fuel and labor cost, travel time for users and air pollution (Tirachini, 2013).

As a case study by using the Kalman filter traffic characteristics after the special events and predicted travel time after graduation ceremony were investigated. Test vehicles equipped with AVL systems were used for data collection and predicted travel time at a given instant of time was determined from predicted and observed travel times in the previous time point. Performance of the model was acceptable due to the prediction error (Yang, 2005).

A method to predict travel times based on the Probe Bus Fleet (PBF) was described. This Probe bus fleet was established by all buses moving bus line. Real-time data collected from probe buses could be used to predict the next arrival time using the Kalman filter. These experimental results showed that this model would provide a higher level of accuracy and reliability of the expected travel time in cases where traffic conditions are constantly changing (Gao et al, 2009).

Using GPS-based data a multiple linear regression model and an artificial neural network model were developed to predict travel times of buses. The models have been used for a case study of bus routes in Chennai, India. The study showed that artificial neural network model outperformed the multiple linear regression model (Ramakrishna et al, 2006).

As another example an urban bus route in China was studied and presented two neural network models for predicting arrival times of buses at the station using the global positioning system and automatic fare collection system data. The results showed optimum performance of these models to present the bus arrival time (Lin et al, 2013).

To estimate travel times for bus rapid transit system, a model was developed based upon support vector machine and by using Kalman filter the results were adjusted.

Vehicle travel time at peak and off-peak hours in the morning was predicted using both models namely the proposed hybrid model and Kalman filter model. The results showed that the proposed model is more appropriate to predict travel times (Xumei et al. 2012).

The problem of limited network sensor coverage caused by insufficient coverage of probe vehicles or limited fixed sensors were solved. By using travel time correlation and the concept of neighbor links dynamic models that were capable of estimating real-time travel times on links not covered by sensors in Kuwait City were developed. VISSIM micro simulation model also was developed to investigate the impact of probes (moving sensors) penetration rate on travel time estimation accuracy and links coverage. The results showed that the dynamic model was feasible, applicable and provided a satisfactory accuracy (Alrukaibi et al, 2018).

Using support vector regression (SVR) models a method with reasonable accuracy was presented to predict travel time on urban arterial roads. In this method by taking advantage of data collected from Bluetooth sensors placed at specific locations on an urban arterial corridor in Chennai, travel time was estimated and the optimum number of inputs, appropriate kernel function, cost parameter and width of tolerance for the SVR model were determined. The results showed that the SVR performed better than an Artificial Neural Network model (Philip et al, 2018).

3. Data Collection and Analysis

A large portion of the required data was collected using Automatic Vehicle Location (AVL) system. In these systems, GPS receivers are installed inside the buses and are connected to the data recording center through telecommunication media. The arrival and departure records of bus at each station are the most important registered records by them. Eventually, the collected data set can be used in presenting Expected Time of Arrival (ETA) models (Gurmu, 2010). The data collection process in this system is shown in figure 2.

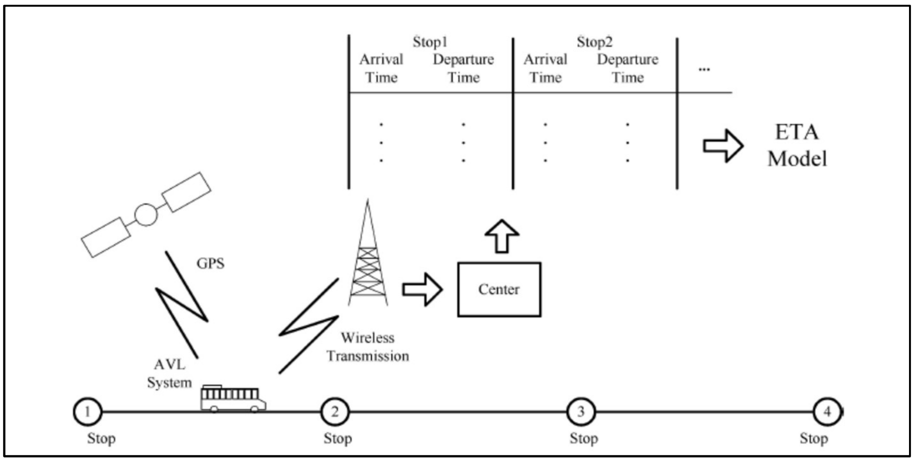

Figure 2: Data Collection Process in AVL System.
Source: (Chung and Shalaby, 2007).

Tehran BRT line 1 between Tehranpars Intersection and Azadi Square with a length of 18 km which connects the east of Tehran to the west was selected as the case study. The route between two consecutive stations in both way and return directions is called a section. West to east of the route is as way direction and west to east as return direction. This line has higher records compared to other lines, and both directions in most of the route have median bus ways. Moreover, there are 14 signalized intersections in each way and return routes and the give-ways system has not been used there. This line has the highest rate of daily passenger transfer among all BRT lines of Tehran and is shown in figure 3.

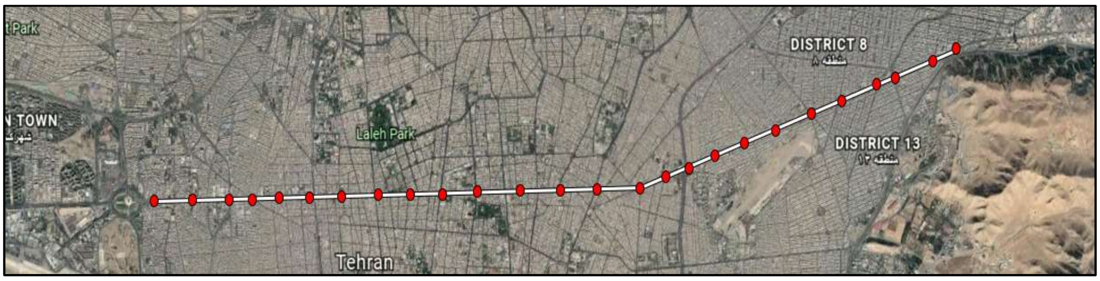

Figure 3: Tehran BRT Line 1

The used data set are collected from March to June 2019 in two peak hour ranges, morning and afternoon (7-9 am, 15:30 to 17:30 pm) at work days (Saturday to Wednesday). Furthermore, it has covered the whole studied route, in both directions. The collection of raw data and conversion of them into a proper format are as follows, briefly:

1. AVL raw data set for Tehran BRT-Line 1 within the desired time were received from Tehran Traffic Control Company. The raw data format was .BAK.
2. Microsoft SQL Server Management software was used for .BAK format. Raw data were entered in this software for observation and examination.
3. SQL Server commands were used for observation and examination purposes. Afterwards, the outputs were taken. These outputs format can be read in Excel software.

Moreover, other required data including the number of signalized intersections and unsignalized intersections between two consecutive stations, through the entire route in both directions were obtained from field observation. The distances between stations which were another required data were received from Tehran Traffic Control Company.

After entering the raw data in Excel software, the analysis and processing were started in order to obtain the required samples for travel time prediction model development. Since the collected data in this research are based on travel time prediction between two consecutive stations, the taken samples include the amount of travel time between two consecutive stations (one section) in both way and return directions and the variables affecting it. In addition to travel time between two consecutive stations, these samples include the average dwell times at origin station, the distance between two consecutive stations, number of signalized intersections in each section, number of unsignalized intersections in each section, average speed, section number, direction (way or return) and the time of day (morning or afternoon). The definitions of each primary independent variables are mentioned in table 1. By omitting some of outlier samples from the rest of them, 219 valid samples were obtained.

Before using collected data, it was divided into two types of training data and validation data. Training data was used to determine the architecture, coefficients and parameters of models, and validation data was used to evaluate the ability of each model to predict and compare the accuracy of predictions. Although there is no rule to divide the data into training and validation data, but as with many studies, the division of data has been done on a ratio of about 80 to 20 (170 samples of training and 49 samples of validation) and has been randomized.

In order to assess the effectiveness of each independent variable on the dependent variable, aka travel time, the regression analysis, beta coefficient and significance degree were used in SPSS software. Significance means that if the corresponding number is lower than 0.05, that variable is acceptable based on the analysis. Furthermore, the more the beta coefficient absolute value of a variable is, the more effective the variable will be.

Table 1: The Characteristics of Primary Independent Variables.

No	*Independent Variable*	*Variable Type or Unit*	*Definition*
1	Distance	Meter	Distance between two Consecutive Stations (Distance of each Section).
2	Signalized Intersections	Numerical	Number of Signalized Intersections in the Section
3	Unsignalized Intersections	Numerical	Number of Unsignalized Intersections in the Section
4	Average Dwell Time	Second	The average of dwell times that were obtained at each origin station
5	Average Speed	Meter/Second	AVL system published speeds in every some second of running status of the bus. This is the average of same speeds in each sample.
6	Time of Day (Morning/Afternoon Peak)	Nominal	Morning Peak Time or Afternoon Peak Time
7	Direction (Way/Return)	Nominal	Way Direction or Return Direction

It should be noted that some of other variables have been considered, but they have not been selected. Some pedestrians can cause disturbance in traffic flow by jaywalking, but since it does not happen on a routine it can be waived. Climate changes might influence on BRT functions. But it can be ignored because these changes are not so sensible. It is plausible for the pavement to have difficulties at some points of the route. This might cause changes in momentum speed of buses, but it can be waived because of its low occurrence.

Subsequently, the results of analysis performed on independent variables will be presented. Significance and beta coefficient of each variable were analyzed and each of the insignificant variables was excluded from the independent variables.

As shown in table 2, at first state that all independent variables were considered, the significance degree of the time of day (morning or afternoon) variable was 0.657, while this number should be under 0.05 in order of the analysis to be counted as acceptable. Moreover, the beta coefficient of this variable shows the slight impact of this variable on the travel time which is the dependent variable. Consequently, this variable was omitted from the independent variables set.

Table 2: Beta Coefficient and Significance Degree of All Primary Independent Variables.

	Independent Variable	*Beta Coefficient*	*Significance*
1	Distance	0.624	0.000
2	Signalized Intersections	0.260	0.000
3	Unsignalized Intersections	0.055	0.010
4	Average Dwell Time	0.327	0.000
5	Average Speed	-0.291	0.000
6	Time of Day (Morning/Afternoon Peak)	-0.010	0.657
7	Direction (Way/Return)	-0.025	0.249

By omitting the direction variable, at second state the analysis was performed on the 6 variables left. In this state, the significance of direction (way or return) variable was the unacceptable amount of 0.214. Simultaneously, the beta coefficient of this variable was -0.026 which showed the low impact of this variable on dependent variable. Therefore, this variable was excluded from the independent variables set. The results of this analysis are shown in table 3.

Table 3: Beta Coefficient and Significance Degree of Independent Variables after Exclusion of the First Insignificant Variable.

No	*Independent Variable*	*Beta Coefficient*	*Significance*
1	Distance	0.622	0.000
2	Signalized Intersections	0.261	0.000
3	Unsignalized Intersections	0.055	0.010
4	Average Dwell Time	0.327	0.000
5	Average Speed	-0.291	0.000
6	Direction (Way/Return)	-0.026	0.214

Finally, in the third case, the analysis was done on the 5 remaining independent variables and the results can be seen in table 4. According to the results, all remaining variables are significantly acceptable and therefore will be used in travel time prediction model development. Given the Beta coefficients, it is obvious that the distance variable has the highest impact on the dependent variable, travel time.

Table 4: Beta Coefficient and Significance Degree of the Chosen Independent Variables

No	*Independent Variable*	*Beta Coefficient*	*Significance*
1	Distance	0.622	0.000
2	Signalized Intersections	0.263	0.000
3	Unsignalized Intersections	0.055	0.011
4	Average Dwell Time	0.332	0.000
5	Average Speed	-0.288	0.000

4. Modelling Using Artificial Neural Network

The term of the neural network refers to a family of models inspired by human brain research. They are networks of nerve cells (Neuron) which their calculations are performed through neurons and connections between them. These networks gained popularity for the prediction of bus travel time due to their ability to solve complex non-linear relationships (Gurmu, 2010). In the following, structure and properties of the utilized neural network will be introduced and finally the results will be yielded.

4.1 Network Architecture Design and Classification of Samples

The most well-known neural network architecture namely Multilayer Perceptron (MLP) was selected in this study because it can roughly estimate any function. ANN architecture typically consists of a set of nodes and connections that are arranged in layers. In this study an input layer, a hidden layer and an output layer were used. It has been proven that a hidden single layer is sufficient for artificial neural network to estimate any non-linear function (Gurmu 2010). The number of neurons in the hidden layer was considered in 18 cases (from 3 to 20 neurons). 60% of the existing samples have been used as the training set, as well as 20% as a testing set and 20%, as the validation set for the development of the neural network.

4.2. Activation Functions

Activation function determines the relationship between the input and output of a neuron network. In this study, six different modes of combining dual functions of Tansig, Logsig and Purelin were used. Given that the number of neurons varies from 3 to 20 neurons (18 cases), it is concluded that 108 various networks implemented and finally the network with the best performance was obtained.

4.3. Training Function

Learning is a process by which neural network corrects its weights in response to the neurons input. Back-propagation neural network algorithm is probably the most popular for use in the transportation engineering (Gurmu, 2010). Previous research also, showed that the Bayesian Regularization training function and Levenberg Marquardt Back-propagation training function had a better performance than other training functions (Jeong and Rilett, 2004). In this study the Levenberg Marquardt Back-propagation training function was used.

4.4. Results

The development of the neural network was done and at the end from the 108 implemented networks, a network that its activation function combination is Tansig-Purelin and has 19 neurons in the hidden layer, demonstrated its best performance. The distribution of travel time values in actual and predicted case of training data is shown in figure 4. As can be seen, the coefficient of determination (R2) of the model is about 0.92 that indicates the appropriate validity of the model.

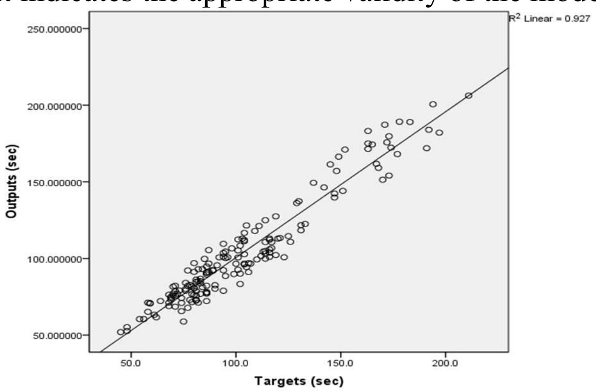

Figure 4: Distribution of Actual and Predicted Values of Travel Time for the Training Data of Network.

Figures 5 and 6 separately show desirable convergence between actual values of validation and also entire collection with the predicted values in the network.

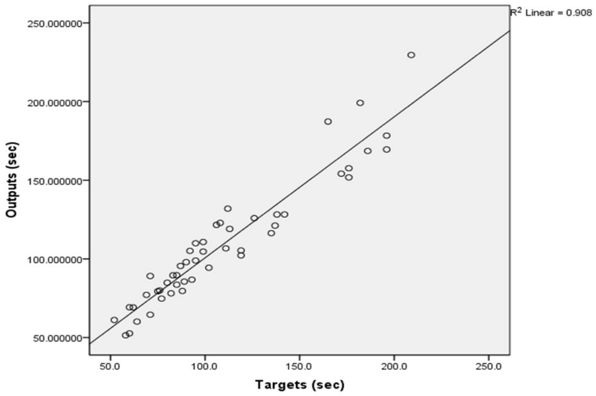

Figure 5: Distribution of the Actual and Predicted Time Values Related to Validation Data in Network

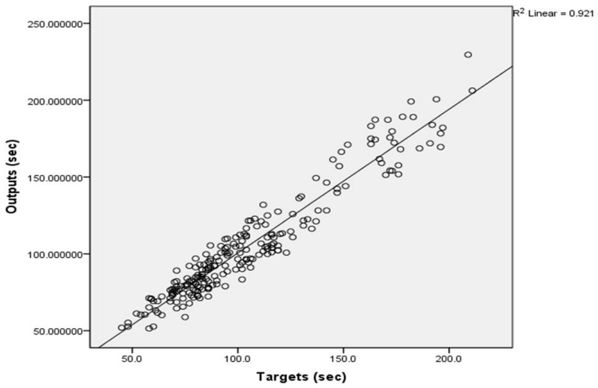

Figure 6: Distribution of the Actual and Predicted Time Values Related to Entire Data in Network.

The learning curve of network is shown in figure 7. Closeness of the curves together and lack of divergence suggests appropriate learning of network and lack of over-fitting and also shows that the network has reached the desirable extension.

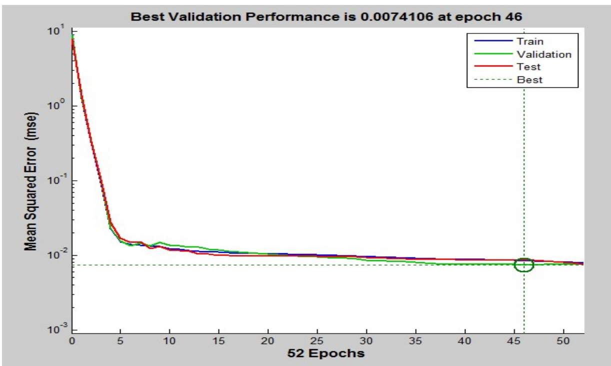

Figure 7: Learning Curve of Network.

5. Modelling Using Linear Regression Method

As mentioned in the previous sections, the neural network was used in addition to the linear regression method. Table 5 presented the final regression model results. The modelling was performed using SPSS software.

TABLE 5. Regression Modelling Outputs

Model	*Unstandardized Coefficients*		*Standardized Coefficients*	*t*	*Sig.*
	B	*Std. Error*	*Beta*		0.000
(Constant)	69.217	6.656	-	10.399	0.000
Average Speed(m/s)	-4.675	0.469	-0.288	-9.962	0.000
AVERAGE DWELL TIME (sec)	1.172	0.077	0.332	15.258	0.000
DISTANCE(m)	0.091	0.003	0.622	28.785	0.000
UNSIGNALIZED INTERSECTIONS	3.710	1.438	0.055	2.580	0.011
SIGNALIZED INTERSECTIONS	11.730	1.297	0.263	9.047	0.000

Therefore, the final regression model to predict the travel time between two stations is expressed by equation (1):

$$Y = 1.172X_1 - 4.675X_2 + 0.091X_3 + 3.71X_4 + 11.73X_5 + 69.217 \quad (1)$$

Where:
Y= Travel Time between two Stations (Second).
X_1= Average of dwell times that were obtained per each origin station.
X_2= Average of some speeds at running status of the bus.
X_3= Distance between two Stations (Meter).
X_4= Number of Signalized Intersections between two Stations.
X_5= Number of Unsignalized Intersections between two Stations.

In order to assess the validity of model, the coefficient of determination (R2), standard error of the regression model and also the amount of Durbin-Watson test were investigated. The results are presented in Table 6. As can be seen, the coefficient of determination in this model is 0.87, which shows the optimal performance of model in travel time prediction. Durbin-Watson test is another measured quantity in table 6. In regression, mostly when behaviour of the dependent variable is studied at a period of time, it is possible that the dependence of errors occurs. This correlation between data set is called autocorrelation. Durbin-Watson test is used to detect the presence of autocorrelation. A value between 1.5 and 2.5 is the optimum result for this test which means that there is no autocorrelation. Applying this statistic, the resulted value was 1.821 which is acceptable since it is within the normal range.

Reasons for using Durbin-Watson test and the acceptable range are as below:

One of the assumptions which is made in regression is independence of errors from each other (difference between real numbers and the numbers predicted in regression equation). If the errors independence theory is denied, moreover the errors have a correlation with each other, then there is no possibility to use regression method. In order to find out about the independence of observations (errors or remaining values independence), Durbin-Watson test is utilized.

Independence concept means that the results of one observation does not have an effect on the outcomes of the other observations. In regression, we may face errors dependence problem mostly when a dependent variable behaviour is studied, this kind of correlation in data is called autocorrelation. In case of autocorrelation existence in errors, linear regression cannot be used anymore.

The output of Durbin-Watson test is between 0-4. If there is no consecutive correlation between the remaining numbers, the value must be close to 2. If it has a value close to 0, it shows positive correlation and if it is close to 4 it indicates negative correlation. Generally, when the number is in the range of 1.5-2.5, there is nothing to worry about.

Table 6. The Values related to Regression Model Validation.

Model	*R Squared*	*Std. Error of the Estimate*	*Durbin-Watson*
Final	0.879	9.4558	1.821

6. Evaluation of the Models

At the end of the study, it is necessary that the accuracy of developed model is evaluated. Therefore, hereafter, the performance of neural network and linear regression models will be evaluated and compared to each other. As it was mentioned before, validation data (about 20% of total data) was used to evaluate and compare the accuracy of proposed ANN and regression models in this paper.

6.1. Evaluation Using R2 and MAPE

The Coefficient of Determination (R2) and the mean absolute percentage error are used as evaluation scales of prediction accuracy for both models. The mean absolute percentage error or MAPE, shows the average percentage difference between actual value (in this case, actual travel time) and predicted value (in this case, predicted travel time) which is obtained by equation (2):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|Actual\ Value - Predicted\ Value|}{Actual\ Value} * 100 \qquad (2)$$

Where n is the number of samples. Furthermore, results of MAPE values investigation of both models are shown in table 7.

Table 7. The MAPE Values of ANN and Regression Models.

Range	*MAPE (ANN)*	*MAPE (liner Regression)*
Entire Route	8.81%	10.52%

As shown, both scales show the superior performance of presented neural network in travel time prediction between two stations, compared to the linear regression model.

6.2. Evaluation Using Absolute Error Scale

By implementing model and comparing the actual and predicted values of travel time, some results about the accuracy of prediction in different sections of route can be achieved. In order to do this, first the absolute error scale was used, which is defined as the difference between the actual value and the predicted value. The details of three predictions done by neural network with highest absolute error are presented in table 8.

Table 8. The Maximum Absolute Errors of Proposed ANN Predictor in the Studied Route.

Section No	*Section Name*	*Route Direction*	*Absolute Error*
18	Valiasr- to - Daneshgah	Way	24.21
17	Ferdowsi- to - Valiasr	Way	22.29
29	Navvab- to - Gharib	Return	20.59

As shown in the table, by applying neural network, sections 18, 17 and 29 have the predicted values with highest absolute error. These sections are on way direction and both have signalized intersections in their routes.

Moreover, the details of three predictions done by linear regression with highest absolute error can be observed in table 9. The results show that sections 29, 5 and 18 of the routes have predicted values with highest absolute error. These sections also have signalized intersections, which cause the accuracy of prediction to descend. Additionally, the results comparison of tables 8 and 9 show that amount of maximum absolute errors predicted by neural network are lower than that predicted by linear regression model.

Table 9. The Maximum Absolute Errors of Proposed Regression Predictor in the Studied Route.

Section No	*Section Name*	*Route Direction*	*Absolute Error*
29	Navvab- to - Gharib	Return	59.26
5	Ayat- to - Pol	Way	59.19
18	Valiasr- to - Daneshgah	Way	37.05

6.3. Assessment and Comparison of the Prediction Process in Various Sections of the Route

In order to assess and compare the prediction process in various sections of the route, validation data were used as well and their actual and predicted values are shown on diagrams. The values of the way direction are shown in figure 8 and the values of the return direction are presented in figure 9. As shown in the figures, defining a certain pattern of the travel time fluctuations derived from both neural network and linear regression over the various sections of the route is difficult. But in general, the prediction accuracy of neural network is higher than linear regression model. Nevertheless, it is observed that in some sections of the route, the linear regression model also has a desirable performance. Furthermore, it is noteworthy that in these figures, the sections with higher proximity of predicted and actual points, are related to the sections of the route that have no signalized intersection; for instance, sections 1, 14, 15, 16 and 24 in way direction and 26, 35, 38 and 44 in return direction can be mentioned.

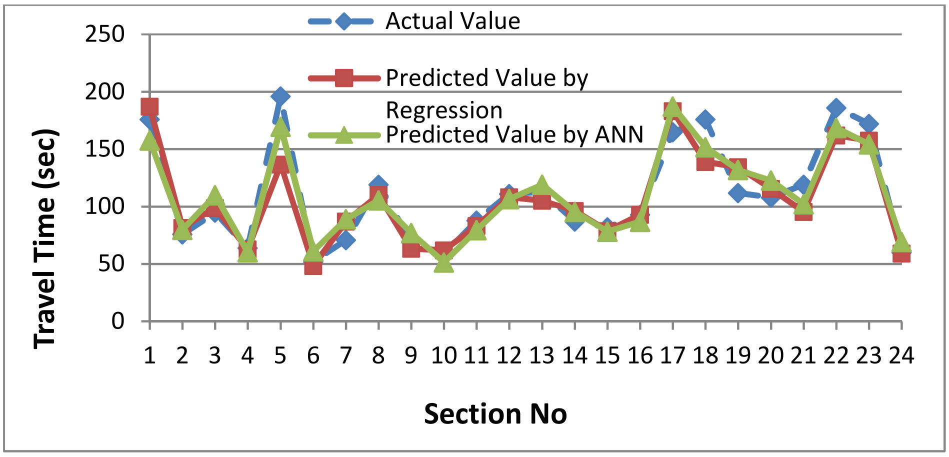

Figure 8: The Actual and Predicted Values of Way Direction Using One Random Sample from Each Section.

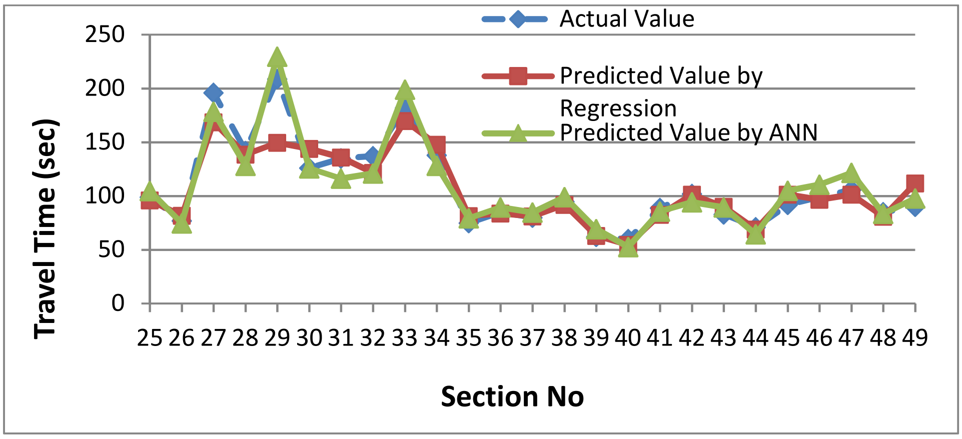

Figure 9: The Actual and Predicted Values of Return Direction Using One Random Sample from Each Section

7. Discussion

Bus Rapid Transit system will be a system with high quality, easy to use, safe, economic and also consistent with environment if it is utilized in the right way. Because of these numerous benefits, this system is spreading in plenty of developed and under development countries. Moreover, it has become to a great interest in recent years. Utilizing this system counts as a suitable solution for spreading public transportation and limiting the use of personal vehicles. But paying attention to the quantity of the system should not bring about ignoring the substantial concept and its quality aspects.

Presenting the travel information to the passengers is one of the most important quality aspects which should be considered. Travel time might be considered as a unique feature which the users pay the most attention to. In other word, travel time is one of the most important factors which influences on travel mode selection in urban transportation system. Hence providing travel time information to the users has great effects on system desirability increase and causes the shift of personal vehicles users towards public transit.

In comparison to the previous researches, we have tried to consider some developments, firstly, in this paper the usage of an Artificial Neural Network has been presented to predict the BRT travel time via AVL data and according to our information there has not been any research of this kind before in Bus Rapid Transit system, secondly, we have considered combination of variables which have not been used like this in the prior studies.

Some parts of the requiring data have been collected by the AVL system which is fundamentally a new data collection scheme in BRT systems in the city of Tehran and the other parts have been collected through filed observation. After that, primary independent variables were studied and meaningful variables were determined via statistical analysis and artificial neural network development was implemented to predict travel time between two stops in BRT system. Moreover, in order to compare results, linear regression method came in use. Function of both neural network and linear regression was studied and a comparison was done between them. Predicted travel time in the various parts of the route was compared to the real data of the travel time.

Finally, it was found out that the presented neural network model does a better function compared to the linear regression model. Since predicting travel time in BRT system is almost a new process, the total performance of the model is encouraging and satisfying. Both models can be used to run a desirable travel time information system and to predict the arrival time of buses at the stops. Performing this system improves BRT reliability hence it causes passengers attraction towards BRT system and helps with the traffic volume decrease in the considered location.

Moreover, it should be added that we have faced some limitations and difficulties in this project which are as follows:

1. Lack of sufficient amount of training time for BRT bus drivers which brings about differences in some factors such as speed, ways of driving (especially at the intersections), delays in opening and closing of bus doors.
2. In some cases, rule breaking pedestrians who crossed the street using the BRT line, caused interference in buses passing and their speed.
3. Ticket selling system troubles in peak hours makes it slower for the passengers to pass the gate, plus the fact that drivers stay longer at the stations in order to use the maximum capacity of the bus, hence increase of the delay time.
4. Improper infrastructure and pavement for BRT buses path and lack of appropriate maintenance causes the road to become bumpy and this makes the buses to decrease their speed at some points of their route which brings about increase in headways.

Meanwhile, these problems plus the occurred delays decrease not only the comfort level of the passengers but also system reliability.

8. Conclusion and future directions

This paper mainly introduces an artificial neural network model and a linear regression model for travel time prediction of bus rapid transit (BRT) system using AVL data. The performance of both neural network and linear regression models were studied and compared. The predicted travel times in both way and return directions were also compared in different sections of the studied route with actual travel times. The results are summarized as follows:

1. The analysis of primary independent variables revealed that the significance degree of the direction variable (way or return) and the time of day variable (morning or afternoon peak) had unacceptable values and so, they had no significant influence on dependent variable, i.e. travel time, and consequently were removed from the set of independent variables.

2. Considering coefficient β, it was found that among the final independent variables, the variable of the distance between two stations had the highest impact and the variable of the number of unsignalized intersections had the lowest impact on the dependent variable.
3. It was shown that both neural network and linear regression models had optimum performance with acceptable prediction precision. Furthermore, a look at the coefficient of determination (R2) and MAPE shows that the proposed neural network had better performance than the linear regression model.
4. The comparison of maximum absolute errors of the models revealed that maximum predicted errors in neural network model were lower than that of linear regression model.
5. Applying validation samples from each section in both way and return directions and the display of actual and predicted values on diagrams shows that the highest number of points where there is a high proximity between actual and predicted values of neural network and linear regression methods are located in route sections where there are no signalized intersections.

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