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Short-term Traffic Volume Prediction for the Merging Roads by Artificial Neural Network

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Abstract: The forecasting of merging road traffic volume is one of the critical issues for the main networks of traffic-congestion suffering cities. Artificial neural network (ANN) – used in many disciplines varying from economy to different engineering applications such as sales forecasting, industrial process control, customer research, data validation, risk management, target marketing and civil engineering – could be a promising solution to this issue. Providing a higher forecasting accuracy based on past traffic data, ANN has become very popular in transportation engineering for the last 30 years. In this paper, the main goal was to predict the short-term traffic volume of a connection road leading to one of Istanbul's Bosphorous Bridge in Turkey by the three different implementations of ANN. These were Feed Forward Back Propagation (FFBP), Generalized Regression Neural Network (GRNN) and Radial Based Function (RBF). Then, obtained results were compared with each other and the result of Multi Linear Regression (MLR) method.

Keywords: Artificial neural network; traffic volume; traffic flow; short-term prediction

Tali Yollar için Kısa Vadeli Trafik Hacminin Yapay Sinir Ağlarıyla Belirlenmesi

Öz: Ana arterlerinde trafik sıkışıklığı yaşanan şehirlerin ikincil derecedeki yollarında trafik hacim tahminlerinin yapılması kritik konulardan biridir. Ekonomiden farklı mühendislik uygulamalarına kadar birçok alanda (satış tahminleri, endüstriyel süreç kontrolü, müşteri araştırmaları, veri doğrulama, risk yönetimi, hedef pazarlama ve inşaat mühendisliği gibi) kullanılan yapay sinir ağı (YSA) bu konuda umut verici bir çözüm olabilir. Geçmiş trafik verilerine dayanarak daha yüksek bir tahmin doğruluğu sağlayan YSA, son 30 yıldır ulaştırma mühendisliği alanındaki uygulamalarda çok popüler hale geldi. Bu makaledeki temel amaç, İstanbul'un Boğaz Köprülerinden birine katılan bir bağlantı yolunun kısa dönem trafik hacmini YSA'nın üç farklı uygulamasıyla tahmin etmektir. Bunlar İleri Besleme Geri Yayılımı (FFBP), Genelleştirilmiş Regresyon Sinir Ağı (GRNN) ve Radyal Tabanlı Fonksiyon (RBF) idi. Daha sonra elde edilen sonuçlar birbirleriyle ve Çoklu Doğrusal Regresyon (MLR) yönteminin sonuçları ile karşılaştırıldı.

Anahtar Kelimeler: Yapay sinir ağı, trafik hacmi, trafik akışı, kısa vadeli tahmin

1. Introduction

It is very important and necessary to estimate future traffic volume with current data in respect of many subjects such as dealing with obstructive traffic congestion, potential threats to ride comfort and driving safety and increasing constrained transportation agency budgets [1]. Prediction of long-

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running traffic volume is particularly vital in terms of determining the main standards of a planned highway such as the number of traffic lanes, their width and dimensioning of pavement layers.

Miscalculation and/or underestimation of long-term traffic volume will result in some large-scaled drawbacks requiring rehabilitation, resurfacing and even reconstruction of the newly constructed highways. The short-term traffic volume prediction implying considerably short observation intervals is generally ranging from 5 to 15 min. It can provide scientifically based traffic information to not only road users to determine their instantaneous travel route/mode and departure time but also to Traffic Management Offices to update their route guidance strategies and other traffic management systems [2]. Hence, traffic engineers and decision makers should painstakingly focus on this issue particularly in metropolitan cities [3].

There are currently various available techniques whose ultimate aim remains the same: to present the short-term traffic flow prediction result as accurate/fast as possible [2]. Grey Markov-Chain, the Grey Model and the Grey-Markov Model are some of well-known mathematical models being applied in all over the world. Current methodologies involving both empirical-based models and traffic process-based models can be categorized in two fundamental approaches: parametric and non-parametric techniques [4]. The former approach dating back around four decades was initially accepted as a milestone to contribute almost an excellent solution to most of time-series related traffic problems, however then it was noticed that this approach was not capable of tackling the problem of the extreme traffic variables prediction [5-7, 4]. Moreover, there were some other lacks detected for instance the historical data could be few, the statistical data could be mutative, many affected factors could be indeterminate, or these prediction models could not be fully adapted for different cases.

As a non-parametric technique, Artificial Neural Network (ANN) is the most commonly applied methodology to forecast transportation variables such as speed, density, travel time, headways but particularly volume and flow. Performing very recent models, this approach is available for analyzing the observed time series and it generates an integrative solution on the given data by training itself [8]. Multi-Layer Perception (MLP), Back-Propagation Neural Networks (BPNN), Feed Forward Back Propagation (FFBP), Generalized Regression Neural Network (GRNN) and Radial Based Function (RBF) are the most widely utilized ANN models in short-term traffic flow prediction [9].

In this paper, short-term traffic volume forecasting was conducted by the last trio of ANN applications and conventional multi-linear regression method (MLR) then results were compared with each other.

2. Previous Studies

Past studies revealed the consistent performance of ANN applications in many areas of transportation engineering. Yang et al. (1992) conducted a study to identify real-time origin-destination matrices for interrupted flows [10]. Dougherty et al. (1992) and Yang et al. (1993) investigated the effect of ANN on the behavioral model of motorist route preference with or without intelligent traveler information systems [11-12]. Ritchie and Cheu (1993) also presented their research into the simulation of freeway incident detection using ANN methodology [13]. Dougherty et al. (1993) investigated the practicability of neural networks to recognize and predict traffic congestion [14]. Hunt and Lyons (1994) studied the role of ANN performance on classification in lane altering modeling and they claimed that ANN provides superior solutions not only to current data analysis but also to other predictive techniques [15]. A case study in the Utrecht, Rotterdam, Hague region of the Netherlands was completed to evaluate the accuracy of short-term forecasts of traffic flow, speed and occupancy by BPNN [16]. The results for occupancy and flow prediction were promising however; forecasts of vehicle speed were relatively favorable most probably due to distorting effect of slow moving vehicles. Kirby et al. (1997) conducted a comparative study between neural networks and statistical models to reveal the fact of short-term traffic flow forecasting on motorway traffic information in France [17]. Cheng et al. (2010) proposed a new approach to deal and analyze the traffic variables, and then evaluated traffic incident detection method based on BPNN [18]. In their investigation of ANN for traffic variables on non-urban highways, Kumar et al. (2013) used a single output forecasting the traffic volume at a single location from inputs which defined 19 separate features of that location from the previous 45 minutes [19]. Their study proved that ANN has favorable performance even in case of increasing time interval for traffic flow prediction from 5 minutes to 15 minutes. Yu et al. (2016) assessed Markov model and BPNN to detect the campus traffic congestion combined with proposed descriptors [20]. Their experimental study pointed out that BPNN-based model yielded to relatively more preciseness and more proper performance.

3. Structure of ANN

ANN is generally utilized to estimate and/or approximate functions which are dependent on many inputs and are most often unknown. Since it is a kind of learning process inspired by anatomical neural systems, ANN can be expressed as a network of interconnected neurons transmitting messages between each other [21]. The fundamental building block of the nervous system is called a neuron. Figure 1 is showing that a neuron consists of a central cell body, dendrites, and an axon [22].

In the human brain, a typical neuron gets signals from others through a host of fine structures called "dendrites". The neuron sends out spikes of electrical activity through a long, thin stand known as an "axon", which splits into thousands of branches [23]. At the end of each branch, a structure called a "synapse" converts the activity from the axon into electrical effects that inhibit or fire activity from the axon into electrical effects that inhibit or fire activity in the connected neurons. When a neuron receives excitatory input that is sufficiently large compared with its inhibitory input, it sends a spike of electrical activity down its axon. Learning occurs by changing the effectiveness of the synapses so that the influence of one neuron on another changes [24].

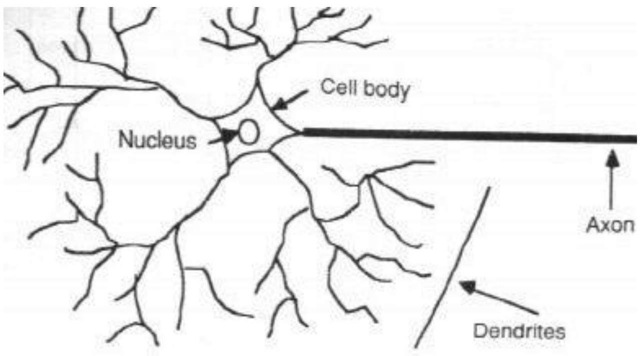

Figure 1. Components of a neuron

Having been likened to biological neural systems, ANNs can be classified into two groups; the first one is feed-forward networks allowing signals to travel only one way; from input to output. They tend to be straight forward networks that associate inputs with outputs. The second one is feed-back networks having signals travelling in both directions by introducing loops in the network. Since their condition is continuously changing until they get an equilibrium point, they are dynamic. In other words, they remain at the equilibrium point until a new equilibrium needs to be found [24].

As shown in Figure 2, the most common type of ANN generally consists of three layers: a layer of "input" units is connected to a layer of "hidden" units, which is connected to a layer of "output" units. The activity of the input units represents the raw information that is fed into the network. The activity of each hidden unit is determined by the activities of the input units and the weights on the connections between the input and the hidden units. The behavior of the output units depends on the activity of the hidden units and the weights between the hidden and output units.

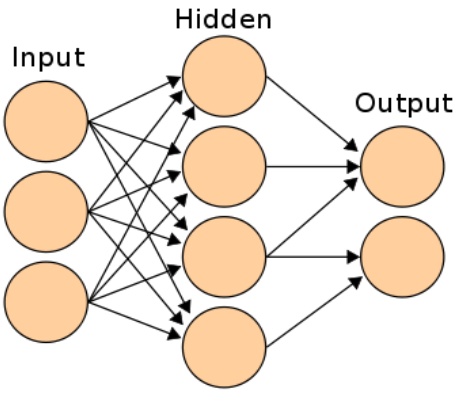

Figure 2. Layers of a neural network

4. Data Collection and Modeling

The data utilized in this study were obtained from a connection road leading to one of Istanbul, Turkey, Bosporus' main structure bridging Europe to Asia (illustrated in Figure 3) which means that this bridge is extremely over-crowded every hour of the daytime. The Bosporus Bridge - known officially as the 15 July Martyrs Bridge - measures 1560 meters long, with a deck with of 33.5 meters and carries around 180.000 vehicles daily in both directions. Beylerbeyi district, located on the Asian shores of Istanbul, has a very close and direct connection road to this bridge as demonstrated in Figure 4. This study included 306 measurements of traffic for 5 minutes on this road. Data samples were collected using video recordings at selected locations for a period of five weekdays between 08.00 am to 06.00 pm.

Figure 3. Location of study area: Bosporus, Istanbul, Turkey

In this study, the obtained database was divided into two subgroups, namely: The first is training subgroup – this is the majority of the collected data, %80 in this case, which is utilized for training the neural networks. The second is test subgroup – the remaining 20% of the input database is assigned for testing. The test subgroup data are only processed through the neural network on completion of the training regime and fitness statistics associated with it are utilized for comparison with the suitability of alternative neural network structures [21].

After extracting the collected traffic data, four models were prepared; these were Feed Forward Back Propagation (FFBP), Generalized Regression Neural Network (GRNN), Radial Based Function (RBF) and Multi Linear Regression (MLR) respectively.

Figure 4. Beylerbeyi's merging road

4.1. FFBP for Traffic Volume Forecasting

FFBP is based upon two main stages. The first stage is feed forward explaining how neural network processes and recalls patterns. During this process neurons are only connected forward [25]. Each layer of the neural network includes connections to the next layer; however there are no connections back. The second stage is back propagation, which is a kind of supervised training, explaining how this type of neural network is trained. When using this method, the network must be provided with both sample inputs and forecasted outputs. The anticipated outputs are compared against the actual outputs for given input. Using the anticipated outputs, the back propagation training algorithm then takes a calculated error and adjusts the weights of the various layers backwards from the output layer to the input layer [26].

During the running of FFBP various activation functions such as "logsig" - a sigmoid logarithmic function, "tansig" - a sigmoid tangent function and "purelin" - a linear function were tested to get most precise results.

a. Activation Functions

Log-Sigmoid (logsig) is a kind of transfer function calculating a layer's output from its net input. This logsig function (N) takes one input and returns each element of N squashed between 0 and 1. In other words, it is clear that this function works between 0 and 1 as seen easily from Figure 5(a).

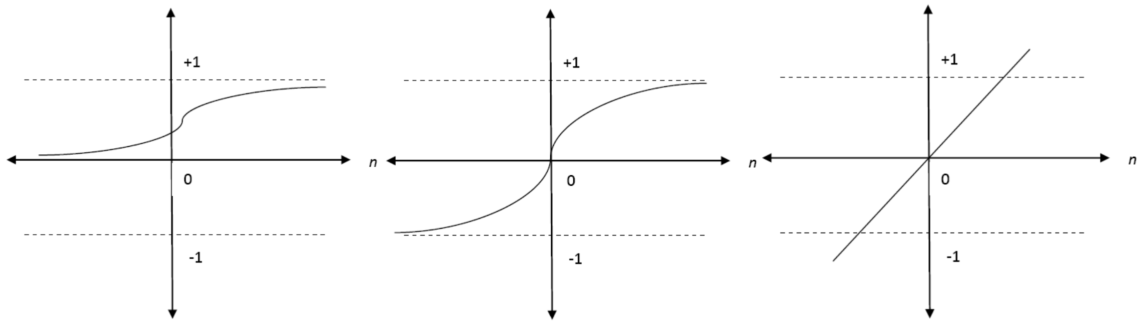

Figure 5. N – SxQ matrix of net input (column) vectors for (a)"logsig" (b). tansig" (c). "purelin"

Tan-Sigmoid (tansig) is also a transfer function. This tansig function (N) takes one input and returns each element of N squashed between -1 and 1. In the light of Figure 5(b), this function works between -1 and 1. The last transfer function utilized in this study is purelin. The purelin is a linear function and it (N) takes one input and returns N. The range of this function is shown in Figure 5(c). The best results in this investigation were obtained from the combination of "tansig" and "tansig". During the running, the number of epochs was 1000. Then the graphs showing the relationship between measured and predicted (simulated) traffic volume were drawn and the equation between them and correlation coefficient "R^2" were calculated as depicted in Figure 6 and Figure 7, respectively.

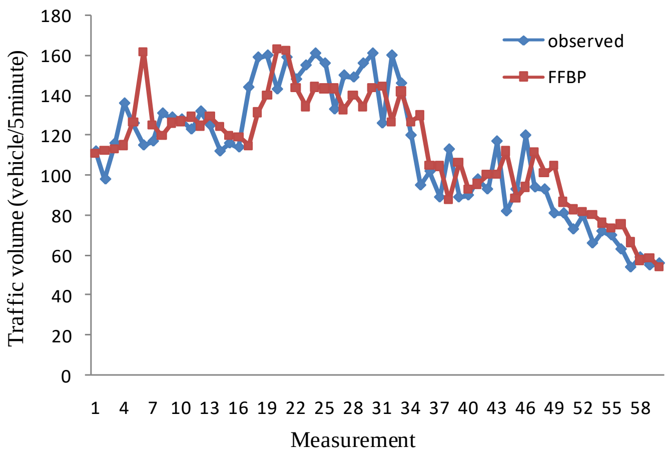

Figure 6. The observed and forecasted traffic volume (by FFBP) for testing stage

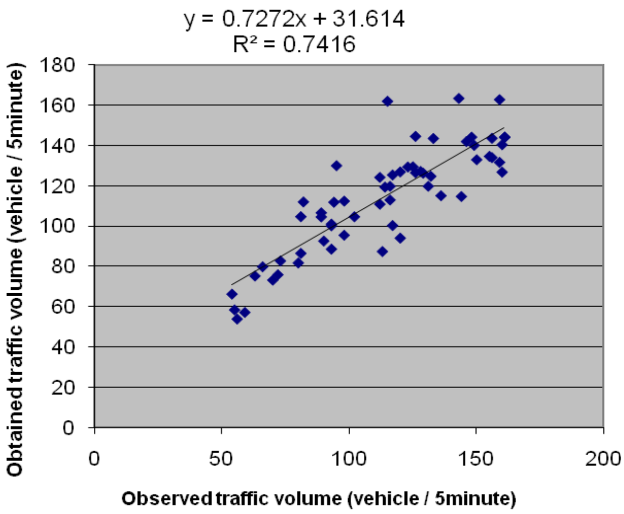

Figure 7. The relevant equation and correlation coefficient for FFBP

4.2. GRNN for Traffic Volume Forecasting

The second method, generalized regression neural network (GRNN) model was first developed by Specht in 1991 [22]. There is no need for any iterative training procedure. This method develops a function between input and output vectors by utilization of training data. When set of training enlarges, square error reaches to zero. This method estimates the probability density function of both independent variable (x) and dependent variable (y) when the set of training is given [27]. During the running of GRNN, in order to accurately predict the results, spread parameter ranging from zero to one was accepted as 0.18 after some trials. Likewise, the graphs showing the relationship between observed and predicted traffic volume were drawn then the equation between them and correlation coefficient "R^2" were found as shown in Figure 8 and Figure 9, respectively.

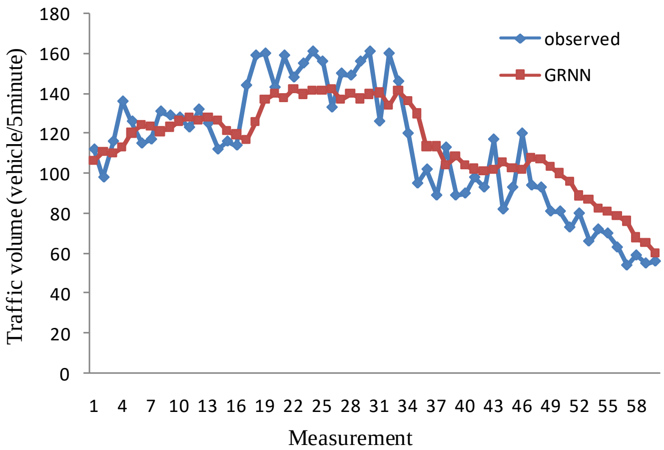

Figure 8. The observed and forecasted traffic volume (by GRNN) for testing stage

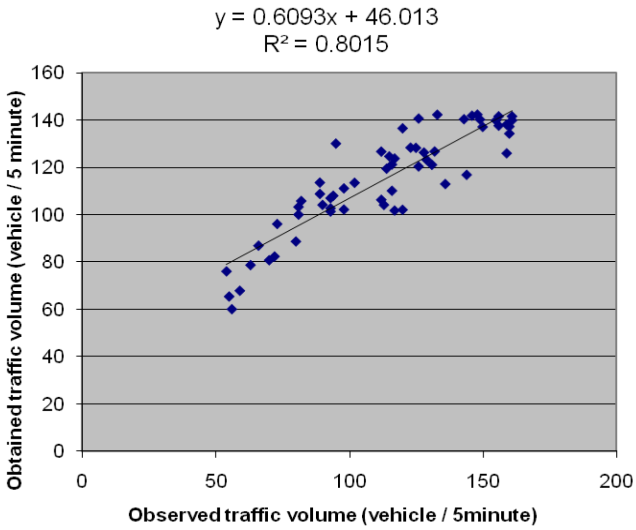

Figure 9. The relevant equation and correlation coefficient for GRNN

4.3. RBF for Traffic Volume Forecasting

The third method, radial based function (RBF) was first developed by Broomhead and Lowe in 1988. This neural network was proposed by the fundamentals of local action-reaction behavior seen in biological neural network system [22].

RBF networks have the advantage of not suffering from local minima since the only parameters that are adjusted in the learning process are the linear mapping from hidden layer to output layer [28].

Linearity ensures that the error surface is quadratic and therefore has a single easily found minimum. RBF is also favorable for estimation problems in case of limited data and overfitting [29]. On the other hand, RBF networks have the disadvantage of requiring good coverage of the input space by radial basis functions. RBF centers are determined with reference to the distribution of the input data, but without reference to the forecasting task. Therefore, representational resources may be wasted on areas of the input space that are irrelevant to the learning task. A common solution is to associate each data point with its own centre, despite the fact that this can make the linear system to be solved in the final layer rather large, and requires shrinkage techniques to avoid over fitting [29]. Similar to previous ANN functions, 80% of the present data was used for the training of the neural network and the rest was used for the testing. During the running of RBF, in order to get the most accurate results, values of SSE (sum squared error) goal to be reached, spread parameter, number of nodes in hidden layer (iterations) and training results showing range were accepted as 0.0001, 0.99, 10, 1 respectively. Similar to previous methods, the graphs showing the relationship between observed and estimated traffic volume were drawn then the equation between them and correlation coefficient "R^2" were calculated as portrayed in Figure 10 and Figure 11, respectively.

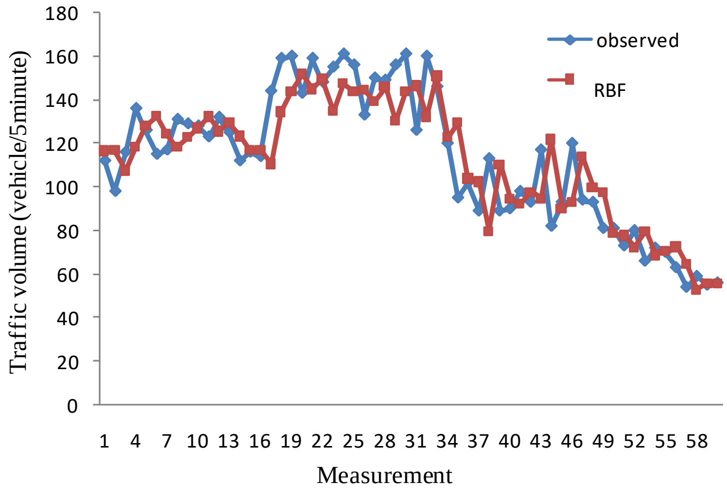

Figure 10. The observed and forecasted traffic volume (by RBF) for testing stage

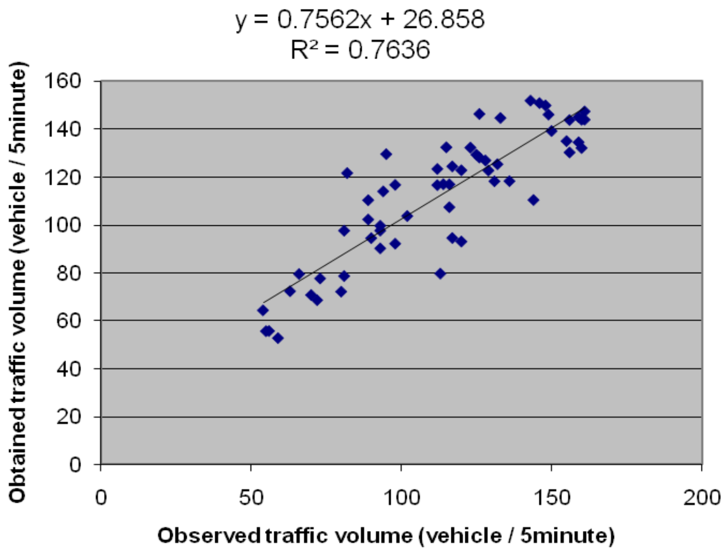

Figure 11. The relevant equation and correlation coefficient for RBF

4.4. Multi Linear Regression (MLR)

The final method, multi linear regression (MLR) attempts to create the relationship between two or more explanatory variables and a response variable by fitting a linear equation to observed data. Every value of the independent variable (x) is associated with a value of the dependent variable (y) [28]. Firstly, auto correlation coefficients were calculated as shown in Table 1. Then, descriptive statistics for training (80% of data), testing (rest) and whole data were found and results were shown in Table 2. After getting coefficients for each intercepts by regression, an equation (Eq. 1) was generated to obtain traffic volume as shown in Table 3 and Table 4. Finally, the graph showing the relationship between observed and obtained traffic volume was drawn and the equation between them and correlation coefficient "R^2" were found as illustrated in Figure 12.

Table 1. Showing the auto correlation coefficients

	Y(t-8)	*Y(t-7)*	*Y(t-6)*	*Y(t-5)*	*Y(t-4)*	*Y(t-3)*	*Y(t-2)*	*Y(t-1)*	*Yt*
Y(t-8)	1.000								
Y(t-7)	0.946	1.000							
Y(t-6)	0.912	0.946	1.000						
Y(t-5)	0.887	0.911	0.946	1.000					
Y(t-4)	0.842	0.886	0.911	0.946	1.000				
Y(t-3)	0.795	0.842	0.886	0.911	0.946	1.000			
Y(t-2)	0.749	0.795	0.841	0.885	0.910	0.945	1.000		
Y(t-1)	0.708	0.748	0.794	0.840	0.885	0.910	0.945	1.000	
Yt	0.663	0.706	0.747	0.793	0.839	0.884	0.910	0.945	1.000

Table 2. Descriptive statistics for training, testing and whole data

TESTING		*TRAINING*		*WHOLE*	
Mean	118.4	Mean	80.21	Mean	87.77
Standard Error	3.351	Standard Error	3.318	Standard Error	2.879
Median	116	Median	77	Median	92.5
Mode	93	Mode	22	Mode	22
Standard Deviation	25.74	Standard Deviation	51.29	Standard Deviation	49.7
Sample Variance	662.7	Sample Variance	2631	Sample Variance	2470
Kurtosis	-1.13	Kurtosis	-1.419	Kurtosis	-1.326
Skewness	0.193	Skewness	0.131	Skewness	-0.131
Range	88	Range	161	Range	161
Minimum	73	Minimum	4	Minimum	4
Maximum	161	Maximum	165	Maximum	165
Sum	6987	Sum	19169	Sum	26156
Count	59	Count	239	Count	298
Largest(1)	161	Largest(1)	165	Largest(1)	165
Smallest(1)	73	Smallest(1)	4	Smallest(1)	4

Table 3 Showing summary output and coefficients

Regression Statistics	
Multiple R	0.95051872
R Square	0.90348583
Adjusted R Square	0.90012882
Standard Error	15.7488059
Observations	239

Table 4. Showing summary output and coefficients

	Coefficients	
Intercept	4.72989513	k
Y(t-8)	-0.05599479	h
Y(t-7)	0.1131498	g
Y(t-6)	-0.10179837	f
Y(t-5)	-0.04604102	e
Y(t-4)	-0.14216226	d
Y(t-3)	0.28397413	c
Y(t-2)	0.07386835	b
Y(t-1)	0.81311629	a

$$\begin{aligned} Y(t) &= a*Y(t-1) + b*Y(t-2) + c*Y(t-3) + d*Y(t-4) \\ &+ e*Y(t-5) + f*Y(t-6) + g*Y(t-7) + h*Y(t-8) + k \end{aligned} \tag{1}$$

Where, Y(t) is dependent variable; Y(t-1), Y(t-2), Y(t-3), Y(t-4), Y(t-5), Y(t-6), Y(t-7), and Y(t-8) are independent variables.

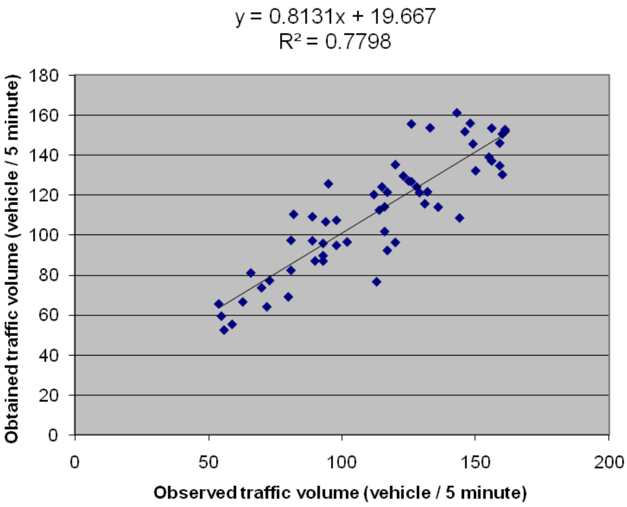

Figure 12. The relevant equation and correlation coefficient for MLR

Finally, mean square error (MSE) was calculated for each method and then the Table 5 showing the each MSE and R^2 value was prepared for a short brief.

Table 5. Showing the MSE and R^2 values

Model Type	MSE [vehicle^2/(5minute)^2]	R^2
FFBP	256.96	0.7416
MLR	225.66	0.7798
GRNN	245.56	0.8015
RBF	234.99	0.7636

5. Discussions and Conclusions

The obtained results were compared in terms of correlation coefficient (R^2) and mean square error (MSE). The R^2 is a measurement of how well the estimated values suit with the actual data. Its range is between 0 and 1. When the strength of the relationship between the estimated values and actual values increases, the R^2 also increases and it converges to 1. MSE is defined as the difference between the actual values and estimated values by the model and it is utilized to determine whether the model does not fit the data or whether the model can be simplified by removing terms.

Both models of ANN and MLR methodology are favorable forecasting methods in transportation engineering. According to the results, it is apparent that GRNN model, one of ANN methodology, is not only superior to other ANN models but also to MLR model in respect to get maximum correlation coefficient. However, the best MSE result was obtained from MLR model. Therefore, anticipation of traffic volume is not adequate by the conventional MLR model, decision makers and traffic engineers should also perform ANN applications to obtain most accurate results.

In conclusion, this study aimed to assess the anticipation of short-term traffic volume by some models. From the results obtained, GRNN and MLR were proved to be promising models to forecast traffic volume in this case study related to a connection road leading to Bosporus Bridge in Istanbul, Turkey.

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