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Research Article

Investigation of Favorable Neural Network Methods to Estimate Traffic Components

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ABSTRACT

Neural networks provide the opportunity to estimate specific components of engineering problems. They are decomposed complex problems into different parts. Thus, it can be easy to compete with each of them through neural networks. In this paper, it was purposed to estimate the average speed of a 6-line road's cross-section by observed traffic variables, such as numbers of vehicles and occupancy values, using radial basis function neural network (RBFNN), generalized regression neural network (GRNN) and the feed-forward back propagation neural network (FFBPNN) models. A comparison was fulfilled between different neural networks and checked against multivariate linear regression (MVLR), a conventional statistical model. After each simulation of neural networks, results show that different forecasts were obtained under the same conditions. The best forecasting is made by FFBPNN, GRNN, and RBFNN, respectively. When compared with multivariate linear regression (MVLR), FFBPNN performs better than MVLR, but GRNN and RBFNN perform lower than it.

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Introduction

The principle of artificial neural networks (ANN) is based on the biological nervous system. The main resource is the human brain and how it processes information. The human brain consists of a very large number of neurons, which of them are completely interconnected. The basic element of each ANN is the neuron. The basic scheme of the neuron is shown in Figure 1. The connection of elements in multiple ways causes different architectures of neural networks [1-2].

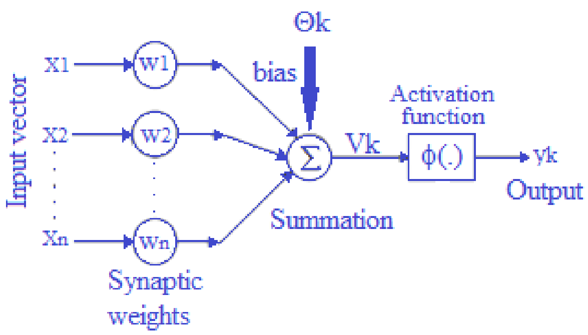

Figure 1. Nonlinear model of a neuron.

The model of a neuron used to create artificial neural networks is shown in Figure 1's block diagram. The bias bk affects the activation function's net input by raising or reducing it. The pair of equations below can be written to represent a neuron k [2]:

$$u_k = \sum w_{ki} x_i \quad (1)$$

$$y_k = \emptyset(V_k + \theta_k) \quad (2)$$

Here, x is the input stimulus, wk is the synaptic weight of the k neuron, Vk is the linear collector output based on the input stimulus, θk is the bias, $\varphi(.)$ is the activation function, and yk is the neuron's output stimulus.

In most cases, short-term traffic flow predictions were made using neural networks for traffic engineering [3–7]. The backpropagation learning algorithm and feed-forward neural networks were most often utilized, along with hybrid methods like neuro-fuzzy and Kohonen maps [8]. Additionally, neural networks were used to estimate the typical travel duration [9–10]. Also, the efficiency of public transportation was predicted by Costa and Markellos in 1997 using neural networks [11]. Furthermore, Celikoglu (2006) used extended regression neural networks and radial basis functions to specify non-linear utility functions for simulating travel mode choice [12]. A radial basis function was utilized by Celikoglu and Cigizoglu in 2007 to estimate the daily trip flows of public transportation [13].

Recently, there have been studies in which different artificial neural network methods are used to solve several transportation problems. These studies examine the use of artificial intelligence technologies and deep learning methods in different aspects of transportation systems including traffic forecasting [14, 15, 16, 17, 18, 19, 20], bike-sharing demand forecasting [21], vehicle destination forecasting [22, 23], traffic flow and speed estimation [24, 25], traffic signal timing [26] and travel time estimation [27], and traffic accident estimation [28]. Most of the research has been carried out using graphical neural networks, deep learning methods, various machine-learning techniques, and different feature extraction methods, especially developed using data with a graphical structure. While these studies show the development of applications of artificial intelligence technologies in transportation systems, they can also guide future research and projects.

The neural networks also do have not prior knowledge of the nature of non-linear functions, but they can approximate solutions. The neural networks are decomposed complex problems into different components. Thus, it can be easy to compete with each of them through neural networks. In this work, it was purposed to estimate the average speed of a 6-line road's cross-section by observed traffic variables, such as numbers of vehicles and occupancy values, using radial basis function neural network (RBFNN), generalized regression neural network (GRNN) and the feed-forward back propagation neural network (FFBPNN) models. A comparison was fulfilled between different neural networks and checked against multivariate linear regression (MVLR), a conventional statistical model. The flow chart of the study is given in Figure 2.

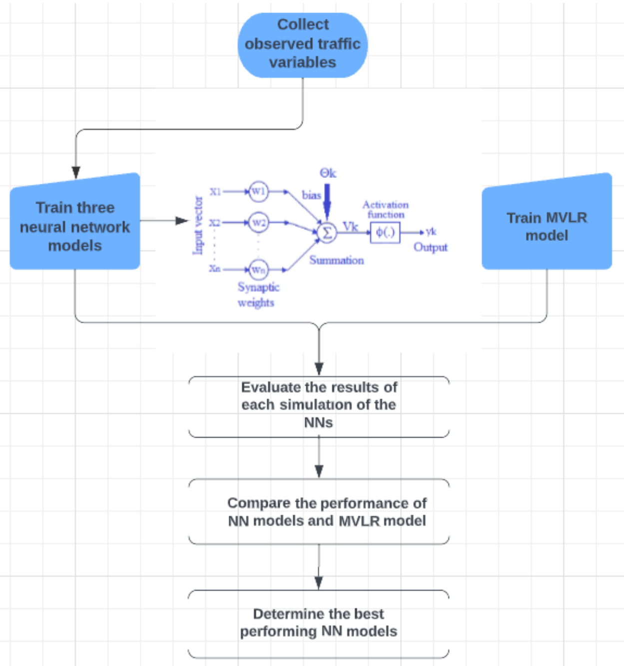

Figure 2. The flow chart of the study

This paper has the following structure. After the introduction, the methodology is summarized in the second section. The comparison of ANN methods for the applied model is presented in the fourth section. Finally, discussion of findings and potential future extensions in the conclusion section.

Methodology

Neural network methods

In the introduction section above, the general working principle of neural networks was tried to be explained by giving the diagram model. For the FFBPNN, GRNN, RBFNN and MVLR methods to be used in this study, the code was written in the MATLAB 2022b [29] and toolbox algorithms/functions were used for the related methods. These algorithms/functions are *"feedforwardnet", "newgrnn", "newrb", "mvregress"* for FFBPNN, GRNN, RBFNN and MVLR, respectively. Detailed theories of the methods involved will not be given here. However, details about these methods can be obtained from the study given in [12].

Error evaluation metrics

In this study, mean-square error (MSE) and R^2 metrics were used to detect and evaluate error values. One of these commonly used metrics, the MSE formula is given in Equation (3).

$$\text{MSE} = \frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2 \quad (3)$$

Here, n is the number of variables, y observed values, and $\hat{y}$ predicted values. A measure of an estimator's quality is the MSE. It is always a positive number that becomes smaller as the error gets closer to zero since it is derived from the square of the Euclidean distance.

Another metric used here is R^2 given in Equation (4). The metric also named the coefficient of determination which is the percentage of the dependent variable's variance that can be predicted by the independent variable (s).

$$R^2 = 1 - \frac{SS_{res}}{SS_{tot}} \quad (4)$$

Here, SS_{res} is residual sum of squares and SS_{tot} is total sum of squares.

Traffic data and analysis

The data of this study were obtained from the sum of the 24-hour-daily Remote Traffic Microwave Sensor (RTMS) data between 01-28 February 2019 in the European side of Istanbul Fatih Sultan Mehmet Bridge before the tollbooths section of the TEM highway. The data was measured with the detector every other 2 minutes at the 6-line road's cross-section during a month. 19388 data were obtained from these observations. A few of these data, edited and processed for analysis, are given as an example in Table 1. The data involves long vehicle (V_L) numbers, private car (V_p) numbers, occupancy (O) values in percent, and speed

(S) values. Due to the calibration of the detector, a few speed data, that measured during the empty line as 240 km/h, was required adjustment. Otherwise, the time series characteristic of data failed. In the estimation problem, 12 input vectors and 1 output vector are purposed. The first 6 input vectors consist of V_L and V_p numbers of per line that are added as in Equation 5. The second 6 input vectors consist of occupancy values in percent per line. The final vector is the output one that calculated the average speed value of the road's cross-section.

$$V_{c(1-6)} = V_{p(1-6)} + V_{L(1-6)} \quad (5)$$

Table 1. Edited and processed data ready for analysis.

Data no.	$V_{p1}+V_{L1}$	$V_{p2}+V_{L2}$	…	$V_{p6}+V_{L6}$	O_1	O_2	…	O_6	S
1	0.16	0.39	…	0.32	0.01	0.05	…	0.02	0.82
2	0.33	0.43	…	0.37	0.02	0.06	…	0.03	0.81
3	0.23	0.33	…	0.32	0.01	0.06	…	0.02	0.81
4	0.19	0.36	…	0.34	0.02	0.05	…	0.03	0.78
5	0.16	0.30	…	0.37	0.01	0.04	…	0.02	0.79
6	0.29	0.37	…	0.26	0.02	0.06	…	0.01	0.82
7	0.29	0.40	…	0.36	0.02	0.06	…	0.02	0.81
8	0.14	0.33	…	0.33	0.01	0.05	…	0.02	0.84
9	0.19	0.46	…	0.34	0.01	0.07	…	0.02	0.83
10	0.19	0.46	…	0.33	0.02	0.06	…	0.02	0.79
11	0.16	0.45	…	0.14	0.01	0.06	…	0.01	0.84
12	0.21	0.33	…	0.25	0.02	0.05	…	0.01	0.80
13	0.23	0.54	…	0.25	0.01	0.07	…	0.02	0.89
14	0.23	0.38	…	0.28	0.01	0.05	…	0.02	0.82
15	0.30	0.40	…	0.29	0.02	0.06	…	0.02	0.80
16	0.34	0.49	…	0.38	0.03	0.07	…	0.03	0.81
…	…	…	…	…	…	…	…	…	…
19386	0.14	0.21	…	0.17	0.02	0.02	…	0.01	0.74
19387	0.11	0.26	…	0.20	0.01	0.04	…	0.01	0.74
19388	0.17	0.25	…	0.26	0.02	0.03	…	0.01	0.78

V_p: private car V_L: long vehicle O: occupancy S: speed

In addition, the central, dispersion and skewness parameters of the data given in Table 1 were calculated. Maximum-minimum values, mean, standard deviation and skewness values of the vehicles are given in Table 2. These values are given in Table 3 and Table 4, respectively, for the occupation and velocity values.

In the problem, the time-series model was not used. The random utility model (RUM) applied that one variable (average speed) is estimated by two other different variables (vehicle numbers and occupancy values) [10, 30]. For comparison, the speed value, obtained from the prediction of the NNs relationship as in *S: f[(*V_L*+*V_p*)), O]*, is compared with the observative one. So, the appropriate configurations of RBFNN, GRNN, and FFBPNN are investigated by simulation. Results are then compared with observations and another comparison by MVLR.

Table 2. Statistical information on the analyzed data set of vehicle numbers.

Statistical V.	Vehicle (V_L+V_p)					
	Line 1	Line 2	Line 3	Line 4	Line 5	Line 6
X_{min}	0	0	0	0	0	0
X_{max}	70	87	83	75	75	76
Mean	15.51	26.42	25.18	26.40	29.94	28.48
Stand. dev.	12.59	16.72	16.69	16.70	18.10	20.32
Skewness	1.26	0.28	0.37	0.12	-0.16	0.00

Table 3. Statistical information on the analyzed data set of occupancy.

Statistical V.	Occupancy (O) (%)					
	Line 1	Line 2	Line 3	Line 4	Line 5	Line 6
X_{min}	0	0	0	0	0	0
X_{max}	100	100	94	90	83	60
Mean	3.28	7.19	8.52	9.04	7.41	4.68
Stand. dev.	6.56	12.18	12.81	12.01	10.05	7.01
Skewness	4.68	4.07	3.88	3.68	3.87	4.08

Table 4. Statistical information on the analyzed data set of speed.

Statistical V.	Speed (S)					
	Line 1	Line 2	Line 3	Line 4	Line 5	Line 6
X_{min}	0	2	0	2	5	9
X_{max}	114	126	134	131	134	147
Mean	71.50	76.96	82.18	77.04	91.51	104.67
Stand. dev.	16.58	17.29	21.27	21.42	19.84	19.52
Skewness	-0.92	-2.49	-1.71	-1.25	-2.35	-1.99

In order to get a better performance, the data of analyses are scaled/normalized between 0 and 1 as which is divided by maximum one. Simulations are written in MATLAB 2022b version [29] and run on a computer with the following properties: Intel(R), Core(TM) i7-4720HQ, CPU@2.60GHz, RAM:16 GB, AMD-Radeon Graphics, 1.0 TB HDD.

Neural networks analyses

Feed-forward back-propagation neural network (FFBPNN)

The FFBP neural network structure consisted of 6 input layers (3-vehicle numbers and 3-occupancy values) and 6 hidden layers (3-vehicle numbers and 3-occupancy values) and one output layer (speed values). Firstly, FFBPNN was run with 19388 data; there was seen high incidence of correct estimation as shown in Figure 3. Since the figure is too long for the whole data, it is clipped and given here for a part of it.

In the figure, it is seen that the velocities decrease at certain intervals. The reason for the decreases is the congestion during the traffic peak hours during the day, as the traffic data consists of observations made around the clock. During the day, the peak hours are 7-9, which is the morning commute, and 17-20, which is the evening after work. During these peak hours of traffic, there may be traffic congestion, especially at bridge entrances and important arteries. This congestion brings along speed drops. In addition, in Figure 4, there is a concentration at certain intervals. Because the speed drops due to peak hour traffic are around 20-30 km/h, which is the reason why the speeds are concentrated at that point. Apart from that, it is seen that it is concentrated between 70-110 km/h points, which we can call the average traffic flow speed.

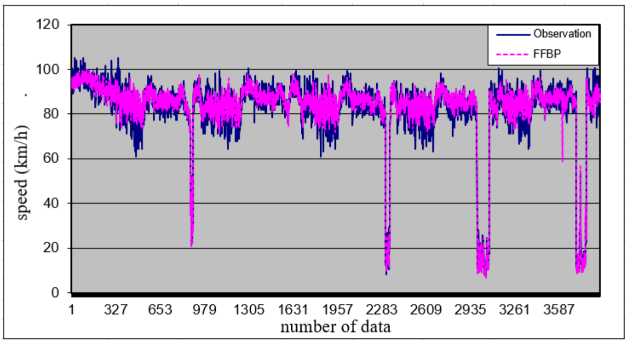

Figure 3. Comparison of FFBP neural network estimation with the observation.

Also, mean square error (MSE) = 20.39 and the coefficient of determination (R^2) = 0.9323 value and regression line can be explained with high accuracy estimating of speed according to observative values as drawn in scatter plot in Figure 4. Moreover, during the analysis, it was understood that changing the input layer and hidden layer node numbers do not affect the estimating performance so much.

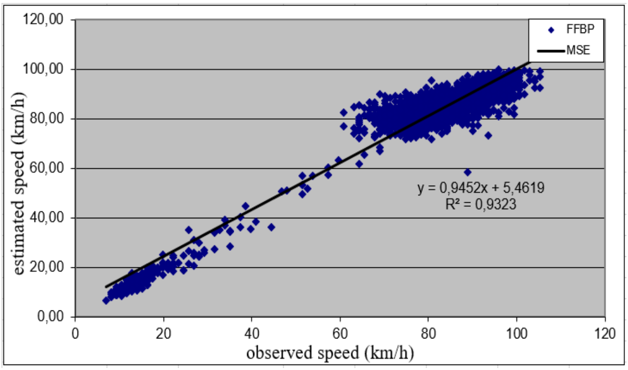

Figure 4. Scatter plot of FFBP neural network estimation.

After the first running, FFBPNN was run with 1250 data, this value is a commonly shared value of RBFNN, GRNN, and FFBPNN analyses. For comparison on an equal basis, that value was selected. Because other than FFBPNN, RBFNN and GRNN could not analyze all data. The data that the three of them ran together was 1250. The range in which the velocity decreases in the figure is from the peak hour congestion in the observed highway region, as explained above. Similar speed drops are seen in other Figures in the next sections as the same data is used.

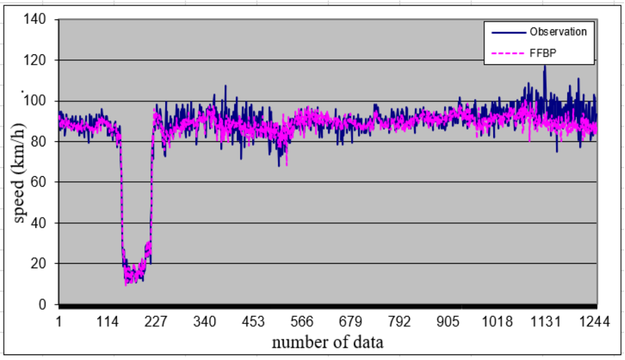

Figure 5. Comparison of FFBP neural network estimation with the observation.

In despite of lower data, analyzing of FFBPNN seems to be closely approximated to observation data as drawn in Figure 5 and Figure 6. The MSE = 24.68 and R^2 = 0.9235 for FFBPNN estimation. Although the observation data decreased from 19388 to 1250, a very successful estimation was made with a very small decrease in the R^2 value.

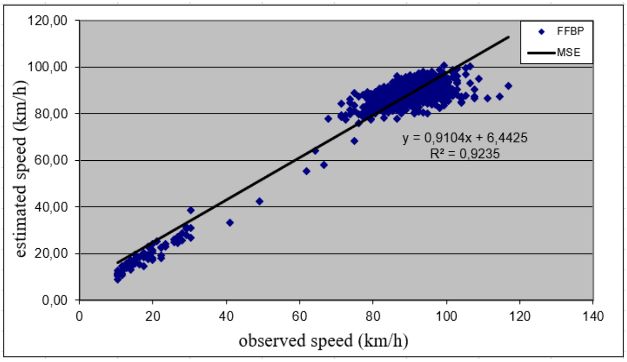

Figure 6. Scatter plot of FFBP neural network estimation.

Radial basis function neural network (RBFNN)

The RBF neural network structure consisted of 6 input layers (3-vehicle numbers and 3-occupancy values) and 6 hidden layers (3-vehicle numbers and 3-occupancy values) and one output layer (speed values).

The RBF neural network could not run for all data (19388). So, we needed to restrict it. The maximum data that RBFNN was run is 1250. The result shows the RBF neural network estimation was not approximated to the observation. As shown in Figure 7, estimating values line does not fit the observative one. Also, the MSE = 211.21 and the coefficient of determination (R^2) = 0.3087, and the regression line are highly different as they are seen in Figure 8.

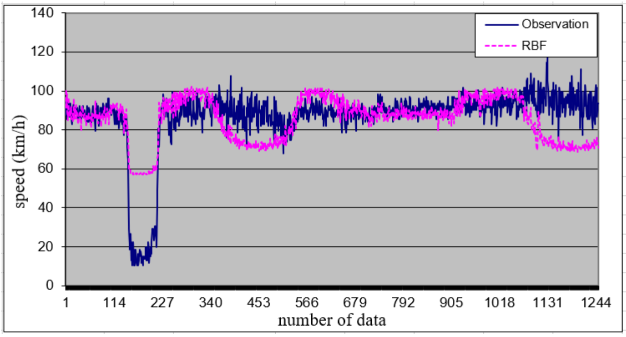

Figure 7. Comparison of RBF neural network estimation with the observation.

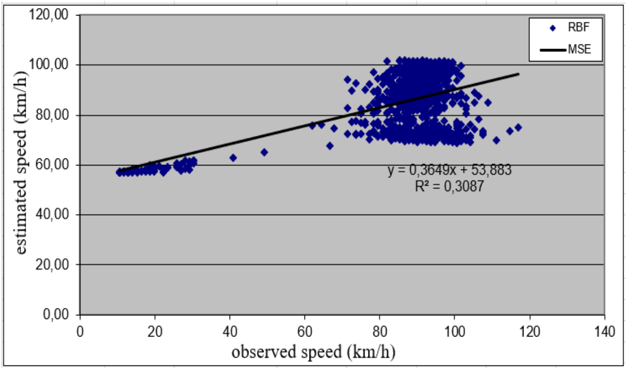

Figure 8. Scatter plot of RBF neural network estimation.

Generalized regression neural network (GRNN)

The GRNN structure also consisted of 6 input layers (3-vehicle numbers and 3-occupancy values) and 6 hidden layers (3-vehicle numbers and 3-occupancy values) and one output layer (speed values).

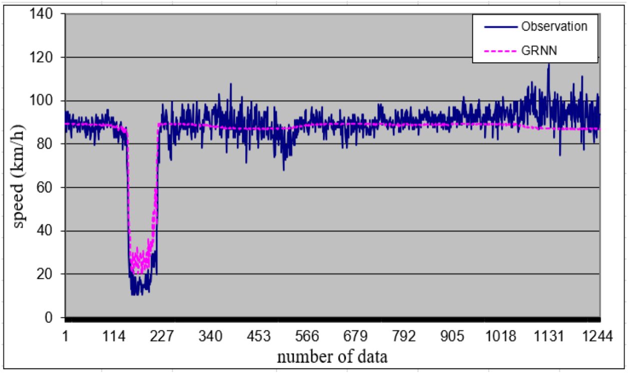

Figure 9. Comparison of GRNN estimation with the observation.

Similar to the RBFNN application, GRNN analyzing could not run the all data. It implemented only 1250 data. But, as a result, forecasting of GRNN was approximated to observed data as in Figure 9. In addition, the coefficient of determination (R^2) = 0.8792 value, regression line in Figure 10, and MSE = 47.26 all indicate that the estimation is highly accurate.

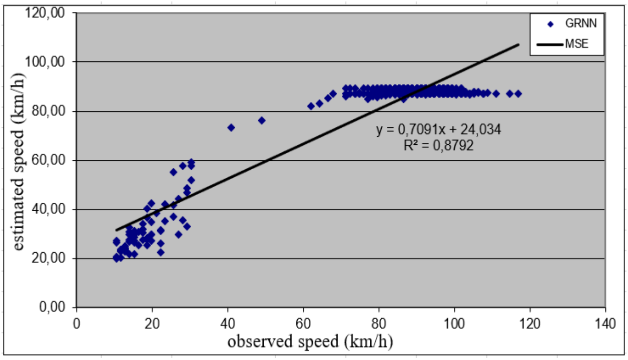

Figure 10. Scatter plot of GRNN estimation.

Multivariate linear regression (MVLR)

MVLR is used to determine the relationship between dependent and independent variables. Due to the correlation between the variables, the relationship is considered to be linear. This technique is used to forecast the behavior of the response variable based on its related predictor factors after multivariate regression has been performed to the dataset. Therefore, in this study, MVLR was used to compare NNs methods.

Multivariate linear regression (MVLR) output shows high consistency with the observative data as shown in Figure 11 and the mean square error (MSE) is 24.54. Besides, the coefficient of determination (R^2) = 0.9116 as shown in Figure 12.

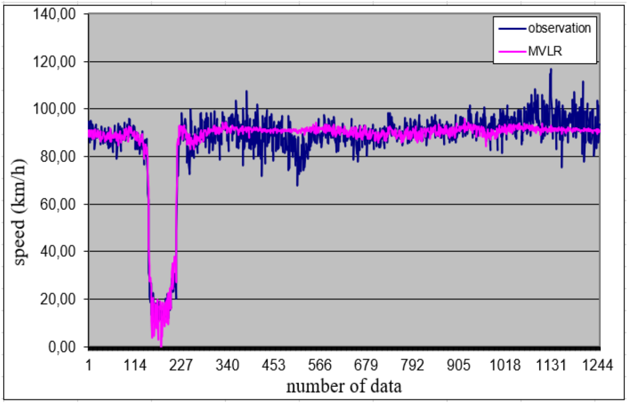

Figure 11. Comparison of MVLR estimation with the observation.

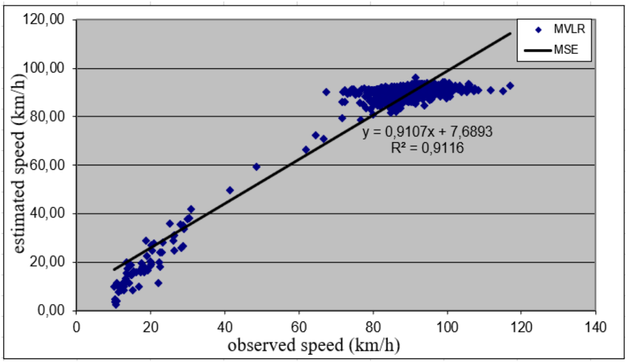

Figure 12. Scatter plot of MVLR estimation.

Comparison of the methods

After each simulation of neural networks, different forecasts were obtained under the same conditions. The best forecasting was made by FFBPNN and GRNN and RBFNN, respectively. However, when MVLR compare with NNs, the performance of MVLR is higher than GRNN and RBFNN, but lower than FFBPNN as it is shown in Figure 13. Moreover, in Table 5, the rankings for the methods are given as a result of the comparison made depending on the MSE and R^2 values.

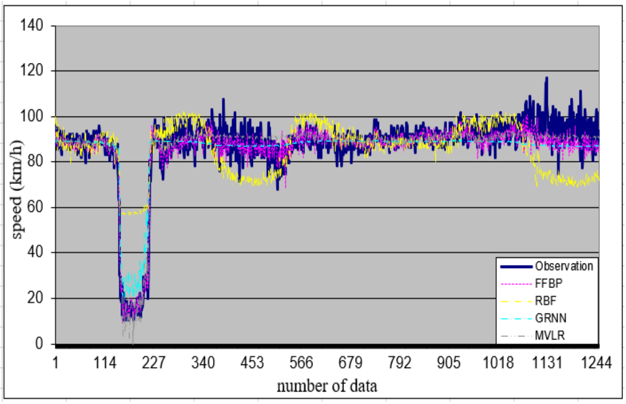

Figure 13. Comparison of all methods.

The FFBP neural network only one that could run the all data. In spite of lowering data from 19388 to 1250, there is a little difference between high accuracy estimation as shown in Figure 4 and Figure 6. Although the data decreased by almost 94%, the prediction success remained almost the same as can be seen from the R^2 value.

Since the features of the computer used in this study are not capable of performing big data analysis for all NN methods, the data set has been reduced. Although this is one of the limitations of the study, it is especially worth emphasizing here that FFBPNN performs better for small data. As the number of data increases, the performance of the methods used may change.

Table 5. Forecasting methods and success rankings.

Comparison of NNs and MVLR			
Rankings	Analyses Type	MSE	R^2
#1	FFBPNN	24.68	0.9235
#2	MVLR	26.54	0.9116
#3	GRNN	47.26	0.8792
#4	RBFNN	211.2	0.3087

Conclusions

In this study, data estimation of neural network methods, which are widely used in traffic engineering and autonomous systems, has been investigated. For this, the traffic data obtained as a result of the observation was used. As a result of the analyzes made for FFBPNN, RBFNN and GRNN, the following results were obtained;

- When compare multivariate linear regression with NNs, performation of MVLR higher than GRNN and RBFNN, but lower than FFBPNN.
- The FFBP is the only neural network that can run all data. It is a great advantage that it can run large data without a high-specification computer infrastructure and predicts with high accuracy.
- The R^2 value of the estimation made with 19388 data in FFBPNN was 0.9323, and the R^2 value of the estimation made with 1250 data was 0.9235. As can be seen, although the data set was reduced by 94%, the estimation accuracy was almost the same.
- Due to the properties such as easy application, short training duration and coding in a short time, and high accuracy estimation, FFBP is more feasible than the other neural networks applications to conventional stochastic and statistical methods in estimating studies.
- In future studies, research can be made for neural network methods that have been popular recently such as probabilistic, and convolutional neural networks.

Ethics Committee Approval

There is no need to obtain permission from the ethics committee for the article prepared.

Conflict of Interest Statement

There is no conflict of interest with any person / institution in the article prepared.

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