Estimation Model of Two-Lane Rural Roads Safety Index According to Characteristics of the Road and Drivers' Behavior

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Abstract

Vehicle crashes are amongst the major causes of mortality and results in losses of lives and properties. A large number of the vehicle crashes occur on rural roads. Accidents become more noteworthy in two-lane roads due to going and coming traffic. Therefore, prediction of crashes and their causes are considerably important to reduce the number and severity of the accidents. The safety index is a suitable quantity for determination of road safety degree. It informs us to study the number of accidents in a specific road and time. In this study, safety index of two-lane rural roads is predicted by Artificial Neural Network (ANN), Radial Basis Function Neural Networks (RBFNN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithms using MATLAB software. The number of causes which ends to an accident is related to some parameters. We chose seven new parameters as inputs to the ANN, RBFNN and ANFIS methods that are geometric and statistical values of the roads and one output variable that is the safety index of segments of two-lane rural roads. 5 roads in Ilam Province, Iran, were selected for the case study to train, validate and test the proposed estimation models. Finally, the results show that, it is possible to predict the safety index of two-lane rural roads with a high correlation coefficient and a low mean square error (MSE) in relation to real values. The ANN method has a higher correlation coefficient and lower MSE in comparison to RBFNN and ANFIS methods. The achieved correlation coefficient and MSE for validation of the ANN approach are 0.94 and 0.0086 respectively, and correlation coefficient of 0.845 and MSE of 0.019 for all data.

Keywords: Safety Index, crashes, artificial neural networks, two-lane rural roads.

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1. Introduction

With the advent of motorized vehicles and its quantitative development in goods and passenger transportation, the complex period of adaptation of human society with a new technical phenomenon has initiated. Motorized vehicles have revolutionized road transportation. Additionally, they have brought about many advantages for human life, but these benefits have not been without their disadvantages such as losses of life and property [Ayati, 2000]. Vehicle crashes bring about considerable losses of life and properties and their resulting social, cultural and economic impacts have threatened human societies very vastly. The severity and number of these accidents in developing countries are more noticeable in comparison with developed countries [Ayati, 2002]. The costs emerging from these accidents are increasing globally. These costs include: deaths, injuries and loss of properties on one hand and energy waste, loss of the labor force in the society, mental and economic consequences of fatalities or disabilities in families and the society on the other hand [Mussone, Ferrari and Oneta, 1999]. Regarding the above mentioned issues, determining and providing methods of modeling the number and intensity of accidents and their effective factors in the accident event result in a better understanding and provides us appropriate solutions for reducing the number and intensity of road accidents. The studies show that accidents occur as a result of complex interference of vehicle parts, human negligence, road and the environments. As fatalities and losses of life and properties resulting from accidents in rural roads are much more than the ones in intra-city roads.

In the present study, an optimized Artificial Neural Network (ANN), Radial Basis Function Neural Networks (RBFNN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) algorithms are used to predict the safety index of two-lane rural roads on the basis of new statistical and geometrical features of the roads (characteristics of the road and drivers' behavior). The optimization was performed in the number of hidden layers and the number of neurons in the hidden layers of ANN for having better accuracy in some performance indexes.

2. Literature Review

Accident analysis and accident prevention studies in rural roads concern the role of geometric features of the roads, traffic, climate and geometric conditions in accident occurrence. Iran has 1% of the world's population, while Iran has one out of deaths of road accidents in the world. Therefore, it is important to make the roads as safe places for vehicles and people. We should decrease the probability of accident in roads using identification and prediction of accidents at all parts of the roads. The number of injured people is 10 times higher than the killed ones on the roads yearly. The high percentage of passengers travel on the roads that imply the essential need of a comprehensive study of road safety [Kashani and Mohaymany, 2011].

Identification of effective reasons with huge impacts on the road accidents has attracted attention of many researchers in the field of road safety. It is so important to find the number of accidents that lead to significant injuries or deaths. We also need to identify critical components may help to diminish the number of deaths and injuries in the road accident. Data mining methods are powerful tools to weigh the crucial elements that result in the road accidents to find the correlations between the large amount of input and output data to achieve an accurate model for prediction of output data [Han and Kamber, 2006]. Knuiman studied the influence of median width of four-lane roads on accident rates using negative binomial distribution. The result of this study reveals the declining rate of accidents by increasing the median width. Additionally, wider medians reduce the accident rates of head-on crashes and out-of-control vehicles driving in the opposite directions. The width increase has a high influence on reducing severe accidents in comparison with accidents with property losses only [Knuiman and Council, 1993]. Vogt and Bared developed a series of regression model of negative binomial and Poisson for prediction of accident rates in rural two-lane roads. Predictor variables include traffic volume, percentage of freight-loading vehicles, shoulder width and lane, horizontal and vertical curves, roadside conditions and access density of the route. These models are used for basic accident rates in accident prediction models [Vogt and Bared, 1998]. Moreover, a number of statistical methods have been applied for development of accident prediction models. For instance, artificial neural network is a new method used for predicting the number of accidents. In 1995, it was applied in developing the model of the driver's behavior, maintenance of road surfaces and positioning the vehicles [Dougherty, 1995]. Abdel-Aty et al used a probabilistic neural network to predict accidents in the Orlando rural corridor and showed that at least of 70% of accidents can be correctly predicted using the probabilistic neural network. Additionally, in accident modeling of highways in Taiwan the two models of artificial neural network and negative binomial were used by comparing the efficiency of the two models it was concluded that an artificial neural network is a suitable alternative for analyzing the accidents in highways [Abdel-Aty and Pemmanaboina, 2006]. Akgungor and Dogan also used the models of neural networks and non-linear regression to predict the number of accidents and road casualties in roads in Turkey. They concluded that neural network provides more accurate results than non-linear regression model [Akgüngor, Dogan, 2008]. Bayata et. al also modeled the monthly traffic accidents in the roads of the country and concluded that despite complex characteristics of the accidents, the neural network model is able to provide acceptable predictions in accidents [Bayata, Hattatoglu and Karsli, 2011]. Applications of neural networks in Iran have been reviewed in the literature review. Abed-ol-manafi for prediction of the number of accidents at intersections in Tehran [Abd-ol-manafi, Ahmadi Nejad and Afandi Zade, 2007] and Mahmoodabadi in the estimation of the number of road accidents in Karaj-Qazvin highway and studying the effective factors [Mahmoudabadi, 2010] and also an estimation of the number of daily accidents in road networks in Iran [Mahmood Abadi, Safi Samg Abadi, 2008] neural network have been applied and the outcome of the neural network model was compared with other statistical models. In all of three studies, the neural network model provided more accurate results than other statistical models.

3. Data Gathering and Data Explanation

The data used in this study are categorized under three classes of traffic information, driving violations and the information related to geometric features and statistics of accidents in specific roads. The roads under study are Ilam-Sarableh, Ilam-Saleh Abad, Saleh Abad-Mehran, Ilam-Eyvan and Eyvan-Islam Abad West. All of these roads are two-lane roads and are located in Ilam province.

In order to estimate the safety index as the number of accidents in length, time and through traffic volume, the roads were divided into 2 km segments and the monthly statistics of accidents for each segment were considered. Using average traffic daily vehicles in a month (ADT), the safety index for every individual segment was calculated and was used as a dependent variable. The characteristics of the roads and drivers' behaviors are chosen as 7 new independent variables that we illustrate them in the following parts. All of the data were collected from Road Maintenance and Transportation Organization [RMTO, 2008].

3.1 Traffic Variables and Driving Violations (Statistical Features)

In this study, traffic variables, which are independent variables including average traffic daily vehicles in a month (ADT) and monthly average traffic speed are investigsted. The average number of exceeding the speed limit violations and unauthorized distance (the unsafe distance between the vehicles) in each segment are two independent variables related to driver's behavior.

3.2 Variables of the Geometric Plan (Geometrical Features)

The independent geometric variables in this study are: The number of horizontal curves in each segment when values of direction change at the time of driving that is the total ratio of the horizontal length to horizontal curve radius and segment length (TRLRSL) as shown in Eq. (1), the average longitudinal slope of segment as shown in Eq. (2) and horizontal curves in each segment. This information was collected using aerial maps and Google Earth from the specified roads. It is noteworthy that the geometric features like lane width, shoulder width, etc., which were not considered are equal in all segments so that the safety index is more accurate.

$$TRLRSL = \sum\left(\frac{L_i}{L\ R_i}\right) \quad (1)$$

$$Average\ longitudinal\ slope = \frac{\sum(S_i\ L_i)}{\sum L_i} \quad (2)$$

Where S_i, L_i and R_i are slope percentage, length and radius of horizontal i'th curve. L is the segment length.

3.3 Output Variable

The safety index of each segment is a dependent variable that we want to estimate it based on the 7 geometric features and statistics of accidents in the specific roads. The safety index of the roads is defined as follows:

$$Safety\ Index = \frac{N}{ADT * L} \quad (3)$$

It means the number of monthly accidents of each segment (N) divided by ADT and segment length (L).

4. Methodology

The main idea of this paper is to estimate the safety index of the two-lane rural roads based on the statistical and geometrical features of the roads (characteristics of the road and drivers' behavior). The new statistical and geometrical features are as the inputs of the ANN, RBFNN and ANFIS and the safety index is as the output of the mentioned estimation models. The ANN is optimized in the number of hidden layers and the number of neurons in the hidden layers. The Levenberg-Marquardt method is used for training of the ANN for some advantages in comparison with other methods. The detail of the methodology is brought in the following parts.

4.1 Artificial Neural Network

The application of artificial neural network is prevalent in the recent years. Natural neural networks are one of the wonders, human beings have been confronted with and have tried to use it to make artificial neural networks [Kaveh and Servati, 2001].

4.1.1 Mathematical Model of Artificial Neural Network

An artificial neural network is a mathematical model capable of modeling and making the nonlinear relationship between descriptive variables and dependent ones. This model with the structure of multilayer perceptron is generally comprised of three layers and each layer consists of certain units of processing namely neuron (cell, unit and node). The first layer of each network is called an input layer in which there is the axis of input data. In this layer there is no processing. Additionally, each multi-layer perceptron is made by certain middle layers which are called hidden layers. The number of these hidden layers and the number of neurons in each hidden layer is estimated by a designer and through the process of trial and error. Neurons of each layer normally are related to all adjacent layers through a directed relationship. Information between these neurons is transmitted through these connections. Each of these connections has their unique weight, which is multiplied in the transmission of information from one neuron to the others. Each neuron receives the weighted outputs of $W_{ij}X_i$ from neurons in the previous layer in addition to a special bias value for the neuron that produce the input neuron Net_j as follow [Haykin, 2009]:

$$Net_j = W_{ij}X_i + b_i \tag{4}$$

Where W_{ij} is the connection weight between the node of i and j, X_i is the output of the node i and b_i is the bias node. In order to calculate output Y_j , neurons pass the input from a nonlinear activation function since without a nonlinear activation function in a neural network, it would behave just like a single perceptron that cannot learn and predict properly. Activation function should be differentiable since we must calculate some derivatives in the training section. We choose log-sigmoid activation functions for hidden layer neurons as shown in Eq. (5), that is the most common form of activation function and a linear activation functions for the output layer. [Haleem, Abdel-Aty, 2010]

$$Y_j = f\left(Net_j\right) = \frac{1}{1+e^{-Net_j}} \tag{5}$$

4.1.2 Construction Process of a Model using Artificial Neural Network with Structure of Multi-layer Perceptron

In order to construct a neural network model and use it, the following steps are required:

a. Determination on the Artificial Neural Network Architecture

In this step the number of layers and network nodes, type of network and training functions and transmission are selected. Then, the appropriate software for the network is selected and prepared. We have the feed-forward neural network architecture for this study.

b. Training the Artificial Neural Network by LM Algorithm

Network training means adjusting the values of network weights for several cases regarding the type of algorithm of learning. The weights are up-to-dated so as to by feeding the input, they are able to provide a suitable response. In this study, Levenberg-Marquardt (LM) algorithm was used as the training method. The LM algorithm is performed as follows [Hagan and Menhaj, 1994]:

$$H = J^T J + \mu I \tag{6}$$

$$g = J^T e \tag{7}$$

Where J (Jacobian matrix) is the first derivatives of the neural network errors concerning the weights. H (Hessian Matrix) is used to guarantee the Eq. (8) is invertible. The LM algorithm updates the weights as the following equations:

$$w_{k+1} = w_k - (H_k)^{-1} g_k \tag{8}$$

$$w_{k+1} = w_k - \left(J_k^T J_k + \mu I\right)^{-1} J_k^T e_k \tag{9}$$

$$e_k = t_k - y_k \tag{10}$$

Where g, I and μ are gradient vector, identity matrix and appropriate constant respectively. e_k, t_k , w_k and y_k are error of the neural network, target of the neural network, weights and output of the neural network in k'th iteration respectively. The LM algorithm switches between the Steepest Descent algorithm and Gauss–Newton algorithm. The steepest descent algorithm guarantees convergence by choosing a suitable parameter for increasing the step-size, although it may converge slowly. The Gauss–Newton algorithm is converged near the global minimum point quickly, although it may diverge. Therefore, LM algorithm have the advantages of the both mentioned algorithms [Hagan and Menhaj, 1994], [Fetanat, Shamshiry and Kazemi, 2013].

4.1.3 Radial Basis Function Neural Networks (RBFNN)

Another artificial neural network that its activation function in the hidden layer is a Gaussian function which is related to the difference of the Euclidean distance between the center of radial basis function and the input data is called Radial Basis Function Neural Networks (RBFNN). This kind of the neural network is to find the function F so as to match the output of its network with the target as following equations:

$$F(x) = \sum_{k=1}^{N} w_k\, \psi(\|x - x_k\|) \qquad (11)$$

$$F(x_k) = t_k \ \ , for\ \ k = 1, 2, \dots, N \qquad (12)$$

Where ψ is supposed as a Gaussian function, w_k is weight of output layers, ll . ll is Euclidean norm, x is the input data, x_k is the center of the radial basis function, t_k and target of data in the neural network and N is the number of samples. The center of the radial basis function is calculated by K-means clustering method [Haykin, 2009] and [Chen, Cowan, and Grant, 1991].

4.2 Adaptive Neuro-Fuzzy Inference System (ANFIS)

Adaptive Neuro-Fuzzy Inference System (ANFIS) a nonlinear intelligent mapping from the input space to the output space. ANFIS constructs a fuzzy inference system (FIS) whose membership function parameters are adapted by some rules. Actually, an ANFIS is an adaptive multi-layer feed forward neural-fuzzy network. If we suppose that the mentioned FIS has two inputs (x, y) and one output, we can describe the rules and layers of ANFIS. Then Takagi and Sugeno fuzzy inference system includes two following criteria [Jang, 1993] and [Takagi and Sugeno, 1985].

Rule I: if x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$

Rule II: if x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$

The overall algorithm for ANFIS is as following equation (Figure 1 and Figure 2):

$$O_i^1 = \mu_{Ai}(x) \ \ , i = 1,2 \qquad (13)$$

$$\mu_{Ai}(x) = \exp\left[-\left(\frac{x - c_i}{a_i}\right)^2\right] \ \ , i = 1,2 \qquad (14)$$

$$\mu_{Bi}(x) = \exp\left[-\left(\frac{x - c_i}{a_i}\right)^2\right] \ \ , i = 1,2 \qquad (15)$$

$$O_i^2 = w_i = \mu_{Ai}(x) \times \mu_{Bi}(x) \ \ , i = 1,2 \qquad (16)$$

$$O_i^3 = \overline{w}_i = \frac{w_i}{w_1 + w_2} \ \ , i = 1,2 \qquad (17)$$

$$O_i^4 = \overline{w}_i f_i = (p_i x + q_i y + r_i) \ \ , i = 1,2 \qquad (18)$$

$$O_1^5 = \sum_i f_i \overline{w}_i = \frac{\sum_i w_i f_i}{\sum_i w_i} \ \ , i = 1,2 \qquad (19)$$

Where x is input to node i, O_i^1 is membership grade of fuzzy set A_i, μ_{Ai} and μ_{Bi} are called Gaussian membership function, a_i , c_i pi , qi and ri are the arbitrary parameter.

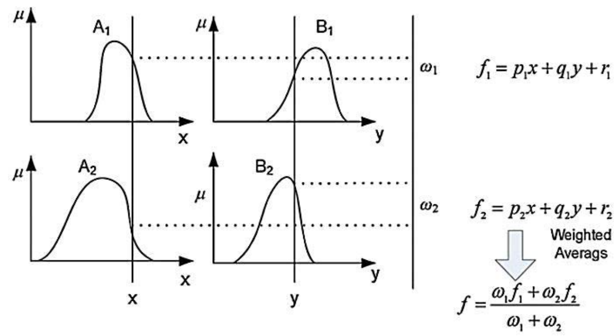

Figure 1. First-order Sugeno fuzzy model

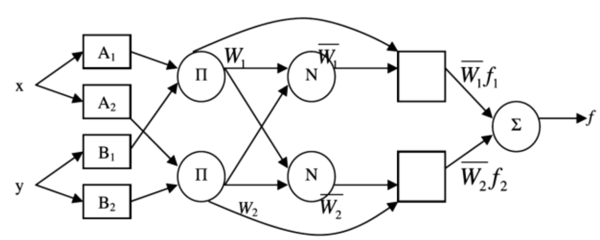

Figure 2. ANFIS architecture

4.3 Assessment of Estimation Models (Validation Process)

After the training step is finalized, in order to ensure the desired performance of the networks will be validated, the algroithms will be performed on a series of new data. The network performance indexes are evaluated. If we don't have suitable value of performance indexes we must adjust the parameters of the models again to get appropriate results in the validation process. After this step the network is ready to be used. The performance indexes are mean squared error (MSE) and correlation coefficient (R) as follows:

$$MSE = \sum_{i=1}^{N} \frac{\left(Y_{real} - Y_{predict}\right)^2}{N} \qquad (20)$$

$$R = \frac{\sum_{i=1}^{N} \left(Y_{predict} - Y_{pmean}\right).\left(Y_{real} - Y_{rmean}\right)}{\sqrt{\sum_{i=1}^{N}\left(Y_{predict} - Y_{pmean}\right)^2 \; \sum_{i=1}^{N}\left(Y_{real} - Y_{rmean}\right)^2}} \qquad (21)$$

Where Y_{real} is the real output, $Y_{predict}$ is predicted output, Y_{rmean} is the mean value of real output, Y_{pmean} is the mean value of predicted output and N is the number of samples. It's ideal to have MSE near to zero and R near to one.

4.4 Parameters Selection

In the present study the ANN with LM algorithm with the structure of multilayer perceptron, sigmoid activation function and supervised learning method is used. In ANFIS, the number of membership functions is supposed 2. 90% of the total data is used for network training, 5% for validation and 5% for network testing, Mean Squared Error (MSE), coefficient of correlation (R) between the network output and real values are used in order to select the best model. All of the mentioned algorithms (ANN, RBFNN and ANFIS) have been performed in Matlab software and the stop conditions were to reach to the special pre-defined MSE or maximum number of iterations for each algorithm.

4.5 Data Normalization

As in certain cases all of the parameters in decision making models do not share the same characteristics, it is necessary to normalize or standardize the data to unify them. Provided that the distribution function parameter has a normal distribution function, data standardization method is used and if the data distribution function is close to the monotonous function data normalization method is used. There are various methods for normalization of input and output data of decision making models, the most common one is that collected data are converted to the numbers from 0 to 1 [Fielding, Brenner and Faust, 1985]. In the present study the following equation is used for data normalization, the result of normalization as shown in Table 1.

$$\mathbf{x_{new}} = \frac{\mathbf{x_{old}} - \mathbf{x_{min}}}{\mathbf{x_{max}} - \mathbf{x_{min}}} \qquad (22)$$

Where x_{new} is the , x_{old} is the real data, x_{min} is the minimum of the real data and x_{max} is the maximum of the real data.

Table 1 Statistic concerning real and normalized values of input and output variables for the roads understudy

No	Parameter title	Real values				Normalized values			
1	Horizontal curve	9.8	0	1.93	2.43	1	0	0.197	0.248
2	Length slope	0.053	0	0.034	0.013	1	0	0.617	0.251
3	Average monthly traffic vehicles in day	43245	3567	19173	12100	1	0	0.39	0.3
4	Monthly average traffic speed	91.2	65.6	77.9	5.25	1	0	0.48	0.205
5	Horizontal directional change of vehicle	6	0	2.11	1.46	1	0	0.352	0.242
6	Monthly violations of exceeding the speed limit	1487	22	618	3576	1	0	0.406	0.243
7	Monthly violations of unauthorized distance	2356	79	886	445	1	0	0.354	0.196
8	Safety index * 100000	14.02	1.16	4.49	2.83	1	0	0.259	0.22

5. Modeling Results

In order to choose the most suitable ANN for the assessment of safety index of the roads more than 2000 ANN with various numbers of layers and neurons are evaluated. The some results of the networks are illustrated in this section. We want to minimize the errors (MSE) and maximize the correlation coefficient (R). In fact, we want to optimize the ANN in the number of the hidden layers and neurons in each hidden layer on the foundation of mentioned performance indexes. We change these components in the loops to find the best parameters for the ANN. According to Table 2, the most suitable ANN for estimation of the safety index of two-lane rural roads is the ANN with 3 layers, which there are 2 hidden layers and there are 3 neurons in each hidden layer (row 10 in Table 2) since it has the highest correlation coefficient. The schematic figure of the selected ANN is depicted in Figure 3. As we can see from the Figure 1, the ANN is fed by 7 features of the roads (Statistical Features and Geometrical Features of the roads). It has 3 neurons in the first and second hidden layers and one neuron in the output layer.

Table 2. Various values of correlation coefficient for the ANN with different number of layers and neurons

No.	Number of layers	Number of neurons in hidden layers	R_train	R_valid	R_test	R_all
1	4	[20-20-10-5]	0.93	0.85	0.39	0.9
2	1	[20]	0.63	0.88	0.75	0.65
3	2	[20-10]	0.92	0.6	0.72	0.9
4	3	[20-10-5]	0.9	0.79	0.33	0.85
5	1	[40]	0.82	0.41	0.19	0.79
6	2	[10-5]	0.68	0.74	0.29	0.65
7	3	[20-20-5]	0.77	0.69	0.85	0.79
8	3	[5-5-3]	0.89	0.74	0.65	0.88
9	2	[5-5]	0.49	0.94	0.12	0.47
10	2	[3-3]	0.836	0.836	0.944	0.845

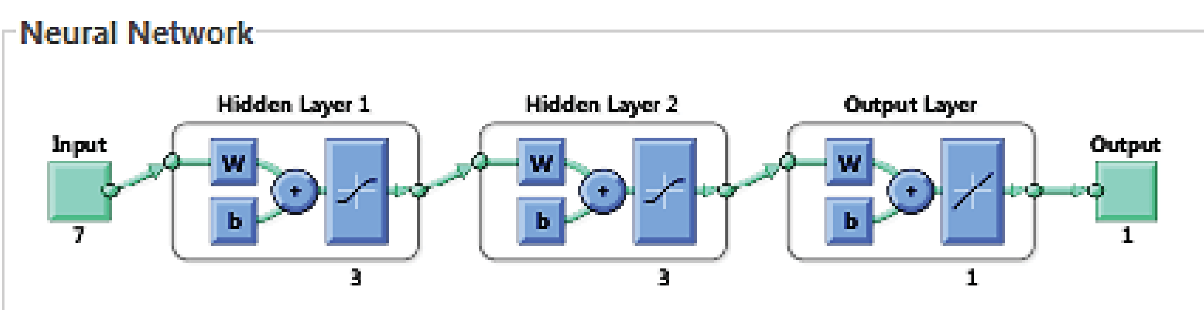

Figure 3. Schematic figure of the selected ANN

The feed-forward neural network is trained by LM algorithm. The neurons in the hidden layers of the selected ANN have sigmoid activation function and the neuron in the output layer has a linear activation function. We performed the ANN with 168 data for 2 km segments related to 5 roads of Ilam province. Each of these 168 inputs have seven independent variables and one dependent variable which were discussed before. One of the output parameters of the ANN is the correlation coefficient between the ANN output and the desired output. It includes the correlation coefficient in network training, network validation and network testing. The correlation coefficient is a mathematical index, which describes the direction and value of the relationship between the two variables. A scatter figure is the best one for illustration of correlation between two variables. These figures which are applied for the present study are depicted in figures 4 to 7. It is worth mentioning that in these figures, the horizontal axis is the desired output and the vertical axis is the output result from the proposed ANN. Figure 4 shows the correlation coefficient for network training. Figure 5 presents the correlation coefficient about the 5 % of input data for validation of the network, which is random and is not included in the training data. Figure 6 shows the correlation coefficient about the 5% of the data for testing of the network, which is randomly being excluded from the training data. Using this figure, the correct level of prediction of the network is estimated. If the correlation coefficient for this step is more than 0.8, according to the experts in the field of the ANN, it is recognized as an efficient and suitable value for prediction.

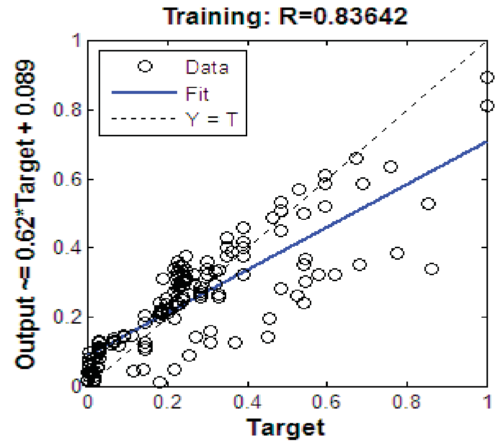

Figure 4. dispersion and correlation coefficient in training data

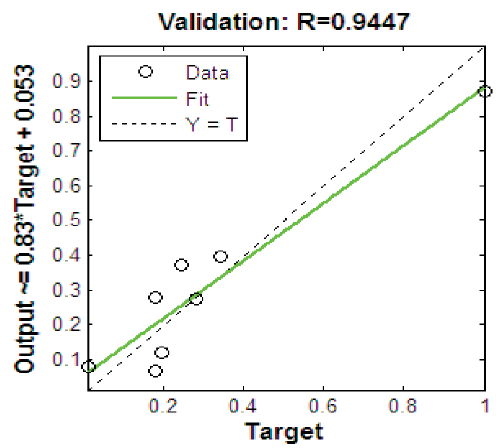

Figure 5. Dispersion and correlation coefficient in data validation

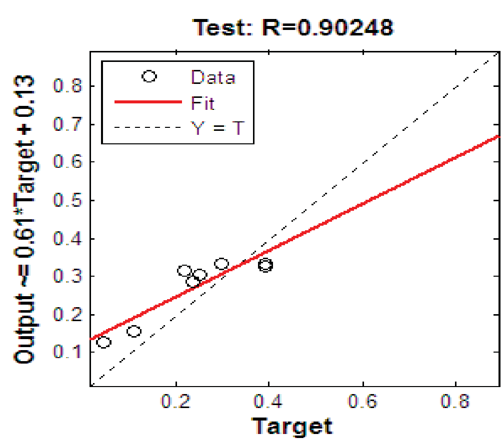

Figure 6. dispersion and correlation coefficient in the test data

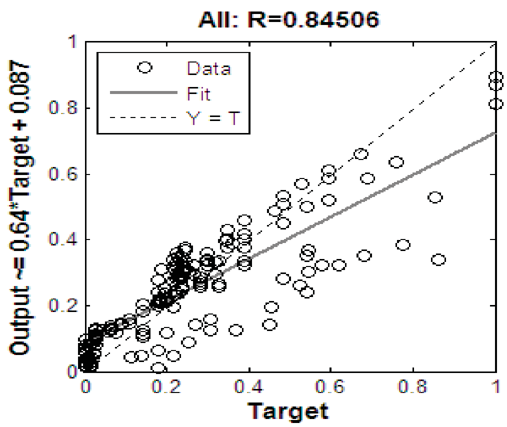

Figure 7. dispersion and correlation coefficient in all of the data

Figure 7 depicts the correlation coefficient for all data (train, validation and test data).

In the present study this coefficient is equal to 0.90 in testing of the network and 0.84 for all data (training, validating, and testing) in network, which is considered as a success. One of the other outputs of the network, which makes it possible to assess the network performance, is MSE. The value of this parameter is depicted in Figure 6. As Figure 8 shows the MSE is equal to 0.0086 in validation of the neural network. The MSE is equal to 0.02, 0.004 and 0.019 in training, testing and all data accidents in the ANN respectively, which show the low error in the estimation of safety index of each segment. Figure 9 depicts the performance index (MSE) of RBFNN approach in each epoch (iteration). We performed the RBFNN algorithm on the training data (90% of all data). The figure shows that the algorithm is converged to mean squared error of 0.01. Then, we test the trained ANFIS on new data to validate and test the proposed method. Table 3 shows the comparison of performance indexes in each method. Each method was tested and the best results were obtained using tuning the parameters of the algorithm. It's clear that the ANN (LM training algorithm) has the lowest MSE and the highest R and ANFIS method has the worst result in MSE and R. We have 168 segments and 208 accidents occurred in these segments. We tested the trained ANN by the 168 segments, which have 7 inputs variable and one output variable. The number of accidents in the artificial neural network's output was 211 in comparison with 208 that is the real value. Furthermore, we have an average of 1.24 accidents in each segment that occurred annually. The ANN predicts an average of 1.26 accidents in each segment, which shows high accuracy of the ANN prediction.

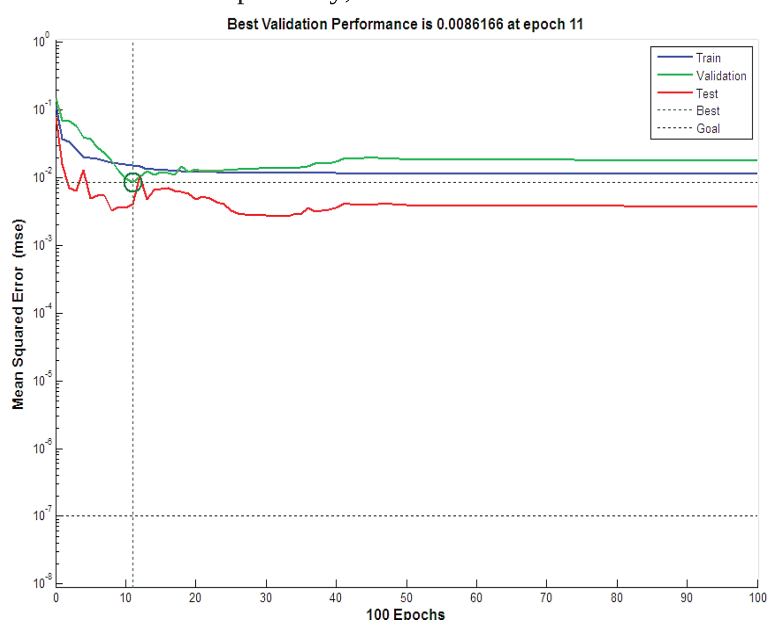

Figure 8. MSE in training data, validation and testing

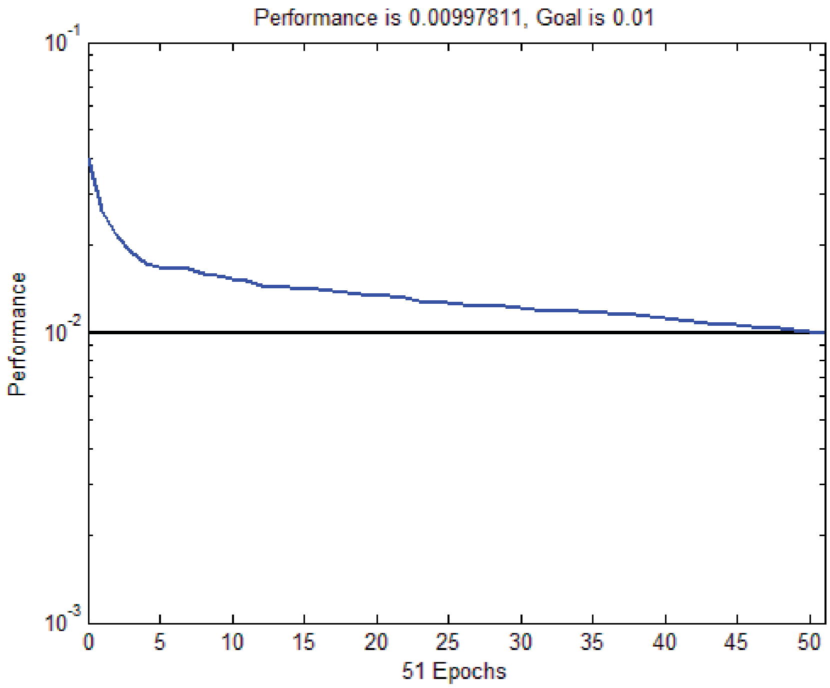

Figure 9. MSE in RBFNN with different number of epochs in training mode

Table 3. Comparison results of the best performance indexes in each method

Methods	Performance Indexes	
	MSE	R
RBFNN	0.027	0.681
ANFIS	0.087	0.614
ANN (LM training algorithm)	0.019	0.845

6. Result Analysis and Conclusion

As figure 4 shows, the correlation coefficient in training step equals to 0.84, in the other word the ANN training was accomplished successfully and the artificial neural network's output is compatible with the desired output. Figure 5 depicts the 5% of input data for validation of the neural network. The value of correlation coefficient for network validation is 0.94, which proves the high accuracy and shows that the artificial neural network's output is very close to the real value.

According to the outputs and the results of figures in testing level, the ANN is able to predict the safety index of two lane rural roads with the accuracy of 0.90 (Figure 6). Using the ANN, it is possible to feed the required parameters as the network inputs that predict the safety index of segments as the network output and determine the number of accidents in each segment. The goal of this study was achieving a tool for estimation of the safety index of the two-lane rural roads based on the new characteristics of the road and drivers' behavior. The comparison result shows that the ANN (LM training algorithm) has the best values in MSE and R (the lowest MSE and the highest R). However, ANFIS has the highest MSE and the lowest R between the mentioned methods. So, the ANN (LM training algorithm) is more accurate compared to the RBFNN and AFNIS methods in estimation of Road Safety Index. As it was discussed, the neural network with a multilayer perceptron structure, sigmoid activation function and supervised learning method with three layers and two hidden layers with three neurons in each hidden layer is able to predict the safety index of two-lane rural roads with a correlation coefficient of 0.94 and MSE of 0.0086 in validating of the neural network and correlation coefficient of 0.845 and MSE of 0.019 for all data (training, validating, and testing).

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