PREDICT STRENGTH OF RUBBERIZED CONCRETE USING ATRIFICIAL NEURAL NETWORK

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Abstract: In this paper, behaviour of rubberized concrete was modelled using artificial neural network ANN and obtained results were compared to experimental data. Experimental test include recycling 5, 10, 15 and 20% percentage of concrete aggregate with different powder size 0.2, 0.4, 0.6, 0.8 mm of rubber. Results demonstrate high ability of ANN in Prediction of compressive strength of rubberized concrete compared to MLR (R^2= 0.9650 and RMSE=0.017). Finally, the performance of each model was evaluated using the Root Mean Square Error (RMSE), Correlation Coefficient(R), Correlation of determination (R2), and Mean Absolute Relative Error (MARE).

Key-Words: Rubberized concrete, Artificial neural network, Multi linear regression, Root Mean Square

1 Introduction

A wide variety of waste materials has been suggested as viable and even beneficial additives for concrete. These waste materials include cellulose, wood lignin, bottom ash, fly ash, and silica fume. Rubber from scraped tires is one of the most recent waste materials that have been investigated because of its potential use in field of construction. [1]. In Iran, only in year 2009, statistics showed consumption of approximately 200,000 metric tons of rubber products which 60% of this (120,000 metric tons) were vehicle tires. These numbers increase every year along with number of vehicles, therefore problems caused by tire will increase as well.

The accumulations of discarded tires can lead to fire and health hazards [2-3]. Tires are often shredded to be used as landfills or to produce tire chips and crumb rubber. Most of tire shredding equipment are mobile and can be easily moved from one scrap tire stockpile or landfill to another one. The shredding process will downsize tire into pieces less than six in2. Scrap tires are used.

in many applications such as controlling erosion in highway [3-5] and asphalt pavement [6-12]. many studies has been carried out in this field such as consideration of mechanical behaviour of concrete filled with different fraction of rubber [13-17] and dynamic experimental [18], in addition, one study has been made in Spain and proved the good potential and performance of rubberized concrete in pavement application after 3 years.

In Some studies, the influence of crumb rubber on concrete itself and size of rubber on compressive and flexural strength of concrete has shown that using coarse grading of rubber crumbs led to lesser compressive strength than the finer grading [20-24].

Fresh concrete properties of this new material such as unit weight and compressive strength were searched. Generally, rubberized concrete is used in pavements, sidewalks, and sound barriers [25–28]. Waste tyres are commonly used in pavements with asphalt [26, 29].

Numerous experimental studies have been dealt with rubberized concrete issues and surprisingly all of them reached similar results. Topc¸u [30] has observed that adding rubber aggregate with ratio of 15, 30 and 45%, will increase fresh concrete’s unit weight, also, increase in amount of added rubber will rise up floatable value. Khatib and Bayomy [31] used assorted size of rubber aggregate in concrete instead of using defined size, and claimed that as the rubber amount increases unit weight of the concrete decreases. Guneyisi et al. [32] in their study, used silica fume content and 2.5, 5, 10, 15, 25 and 50% rubber aggregate in several sizes and observed a fall in unit weight of the concrete in line with the increase in rubber amount. Fedroff et.al [33] has added 10, 20 and 30% rubber aggregate and found that unit weight of the fresh concrete decreases as the rubber amount increases.

For years, researches have used various methods in order to anticipate the concrete properties in advance. In this study, making use of experiments, artificial neural networks (ANN) and linear regression methods were employed in order to forecast the results before performing any test. In order to train network model, percentage of recycled rubber, rubber powder size, and fresh concrete's unit weight were entered as input; compressive strength of rubberized concrete considered as output. After training the networks without entering the experimental results, only experiment input values were used and tests were performed. Consequently, the values obtained were very similar to real values. The network used in ANN method was a multi-layer, feed-forward model that has back-propagation algorithm for error distribution.

2 Experimental procedure

2.1 Materials

Concrete samples that were used here were tow types, some of them made of pure concrete, and others were composed of concrete with particles of scrapped tires. Grated cubic forms for placing fresh concrete with 0.55 water to cement ratio. In order to make fresh concrete ingredient like Ordinary Portland cement (Type I, with density 315 kg/m2), natural sand, and water were used. The largest diameter of the fine aggregate was 2 mm. The Young's modulus and compressive strength of rubber installed in the fresh concrete were 23 and 306 kg / m2 respectively, and cubes had another dimension ranges between 0.2 and 0.8 mm.

2.2 Test specimens

Cubic specimens were prepared in 7 × 7 × 7 cm in size. All samples were moist cured for 28 days at temperatures of 27 º C and relative humidity of 100%. In total twenty-seven specimens were made for the compression test. Samples were loaded manually by the machine while Moving loads have been recorded digitally.

2.3 Test results

Series of test on compressive strength and density of concrete samples and rubberized concrete were made and achieved results are presented in Table 1. Each figure is average of three samples.

3 Theory of Neural Network

3.1 Basic Information

First neural network model was introduced in McCulloch & Pitts thesis (1943)[34], in which they considered human brains as a well-structured computer which is consist of countless neurons. The primal neural network known as Perceptron was introduced by Rosenblatt [35] in 1957. He applied alphaintensification to learning process; however, he could not solve simple nonlinear problems. Hopfield's model [36] & Bolzman machine are amongst crucial models of neural network. A typical neuron network composed of non-linear system with complicate interconnected neurons. These neurons are constituent units of the central nerve system and it can process general communication, and its efficiency can be enhanced through repeated learning. Neural network and Artificial intelligence (A.I) dealing Symbolic use radically different method to approach a certain problem. A.I. that processes neural network and symbolic approaches from radically different paths to a suggested problem.

Developed by Werbos (1988) [37] and other scientists the back-propagation learning algorithm can drill multi-layered perception and has application even in management related issues such as optimum matters, robot control, character recognition, voice recognition, signal processing, and machine vision. While neural network, inspired by a biological system and deals with the systematization of data process system, on the other hand A.I cope with tracing analogy in expressing various types of knowledge in order to solve difficult problems. To apply such a learning function of neural network in engineering problems, McCulloch and Pitts in 1943 devised a mathematical model. Fig. 1 shows a typical neuron model for engineering matter.

A typical neural network process can be described as follow: the signals (x_0, x_1, x_2) come from outside and will be received by activation function and then transmitted to the other neural network, at this stage, weights of activation function (W_0, W_1, W_2) is multiplied to each correspondent signal and will be added together. Equations (1) and (2) show such a process.

$$y = f(net) \tag{1}$$

$$net = \sum_i W_i x_i + \theta \tag{2}$$

where x_i, y, θ and W_i stand for input value ,output value bias and weight respectively. There can be various activation functions f (net) in neural network, although recent trend in use of neuron circuit has shown frequent use of nonlinear function. As transition function, Eq. (3) shows sigmoid function that produces an output value ranging from 0 to 1.

$$f(x) = \frac{1}{1 + \exp(-\lambda x)} \tag{3}$$

There are different types of activation function that control the dynamic reaction of neural network and it ranges from Sigmoid function and log function to segment function, and the Gauss function, which is used in special cases

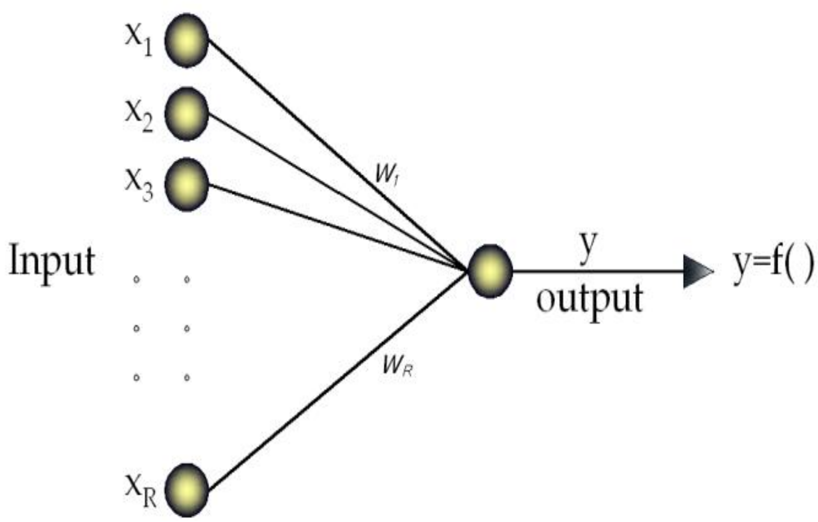

Fig.1 Neuron of McCulldch-Pitts

Table.1 Test Model Specifications

Volume of chip rubber aggregate	Tire particles size	Compressive strength	Density(Kg/m^3)
0%	-	397 Kg/Cm^2	2405
10 %	0.2 mm	238 Kg/Cm^2	2240
10 %	0.4 mm	250 Kg/Cm^2	2310
10 %	0.6 mm	261 Kg/Cm^2	2361
10 %	0.8 mm	276 Kg/Cm^2	2388
20 %	0.2 mm	199 Kg/Cm^2	2111
20 %	0.4 mm	211 Kg/Cm^2	2219
20 %	0.6 mm	233 Kg/Cm^2	2254
20 %	0.8 mm	249 Kg/Cm^2	2305

3.2 Multi-layered Perceptron

Neural network is combination of several layers in which connections of individual neurons are arranged. Multi-layered perceptron, which is subject of this paper, is a neural network that has more than one hidden layer between input and output layer. It is a simple version of neural network models that are widely used in engineering.Actually, Resenblatt's single-layered perceptron, has only one layer for learning, so it was impossible to use the model; also, it was not capable of making a linear separation. To overcome this problem, the multilayered perceptron is introduced. Network is connected to input layer, hidden layer and output layer in one direction. The connection within each individual layer is a freeforward network and Input layer and output layer are not connected directly. Multi-layered perceptron has a similar structure to single-layered perceptron, however, arranging features of each input-output unit and the hidden layer in non-linear format brings more advantages compare to other models, and as a result, the network capability will be enhanced. The following is the formula for a given input in a multilayered perceptron including three layers. In first step, neurons in hidden layer process Equations (4) and (5).

$$y_i = f(net_j) \quad (4)$$

$$net_j = \sum_i W_{ji} x_i + \theta_j \quad (5)$$

Where x_i and y_i are correspondent output for input value and hidden layer, and W_{ji} , θ_j are the weight and bias between input and hidden layer. Esq. (6) and (7) are an operation for the output layer and use the output value of hidden layer yi and output value.

$$y_k = f(net_k) \quad (6)$$

$$net_k = \sum_k W_{ki} y_i + b_k \quad (7)$$

The Y_k is output value of the neural network, and W_{ki} and b_k are weight and bias between hidden and output layer. The activation function between Eq. (4) and (6) does not need to be identical.

Neural network makes an output value through a simple operation and can perform parallel process that enables the model to process data very fast. Drilling a neural network means to have a good control on the connection strength between neurons to produce a set of reasonable output value for given input therefore It is necessary to define error function such as Eq. (8) in drilling in.

$$E = \frac{1}{2}\sum_K (d_k - y_k)^2 \quad (8)$$

In above equation t_k is the target andy_k is output value of a neutral network respectively. The error function, E, is sum of all output value which directly comes from a neural network and set of target value in an output value. Error function can be reduced by controlling the connection strength in neural network

2.1.Learning Algorithm

The most important element that determines the output for specific input is the connection strength. Output value of each processing element also identify the output of complete neural network, therefore to get desired output value it is important to control the connection strength. Here, the learning refers to the process that controls the connection strength among processing elements using the precedent examples of neural network. Various algorithms are in action to drill a neural network. The back propagation algorithm, which is named after its feature, is in use extensively; the learning signal is transmitted from output layer to the hidden layer and it goes back to the output layer. Explanation of the back-propagation algorithm is as following steps:

Step 1: Set the primary weight (W_{kj}, W_{ji}), bias b_j,b_k), learning rate(η), and momentum($\propto$)

Step 2: Compute the generalized error(δ_k) from the output layer.

$$\delta_k = y_k(1 - y_k)(t_k - y_k)$$

Step 3 : the weighted value between output and hidden layer will be added according to the following Eq

$$\Delta W_{kj}(k+1) = \eta \delta_k h_i + \alpha W_{kj}(k)$$

(k stands for repetition step, η for learning rate,$\propto$ for momentum, and h_i for concealment layer and output value)

Step 4 : Compute the generalized error(δ_j) from concealment layer

$$\delta_j = h_j(1 - h_j) \sum_k \delta_k W_{kj}$$

Step 5: Learn a weighted value between output layer and concealment layer

$$\Delta W(k+1) = \eta \delta_j h_i + \alpha W_{ji}(k)$$

Step 6 : Repeat step 1 to 5 if the error function does not reach to a given target value.

3.3 Performance Criteria

To achieve desired optimal network model performance, certain criteria like Root Mean Square Error (RMSE), correlation of determination (R2), Correlation Coefficient (R), and Mean Absolute Relative Error(MASE) have been used in current study. They are given by:

$$\mathrm{RMSE} = \sqrt{\frac{\sum_{i=1}^{N}\left(\mathrm{CS_i} - \widehat{CS}_i\right)^2}{N}} \quad (9)$$

$$R^2 = 1 - \frac{\sum_{i=1}^{N}(\mathrm{CS_i} - \widehat{CS}_i)^2}{\sum_{i=1}^{N}(\mathrm{CS_i} - \overline{CS}_i)^2} \quad (10)$$

$$R = \frac{\sum_{i=1}^{N}(\mathrm{CS_i} - \overline{CS}_i)(\widehat{CS}_i - \overline{\widehat{CS}_i})}{\sqrt{\sum_{i=1}^{N}(\mathrm{CS_i} - \overline{CS}_i)^2 \sum_{i=1}^{N}(\widehat{CS}_i - \overline{\widehat{CS}_i})^2}} \quad (11)$$

$$\mathrm{MARE} = \frac{\sum_{i=1}^{N}|((\widehat{CS}_i - \mathrm{CS_i})/\mathrm{CS_i})|}{N} * 100 \quad (12)$$

Where $\mathrm{CS_i}$ and $\widehat{CS}_i$ denote actual and predict value of compressive strength and $\overline{CS}_i$ the mean of $\mathrm{CS_i}$ values and N is the total number of data sets. First of all the input and output variables are normalized linearly between 0 and 1, use of logistic function (which is bounded between 0.0 and 1.0) makes the normalization to be performed by the following equation.

$$\bar{X} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (13)$$

here $\bar{X}$ is the original data set is the standardized value of the input, X is the original data set, X_{min} and X_{max} are respectively, the minimum and maximum of the actual values, in all observations. The main reason for standardizing the data matrix is that the variables are usually measured in different unit therefore standardizing the variables and recasting them in dimensionless units will remove the arbitrary effect of similarity between objects.

4 RESULTS AND DISCUSSION

From the overall exercise above, the possibility of using artificial neural networks for compressive strength prediction was demonstrated and the following important observations were made.

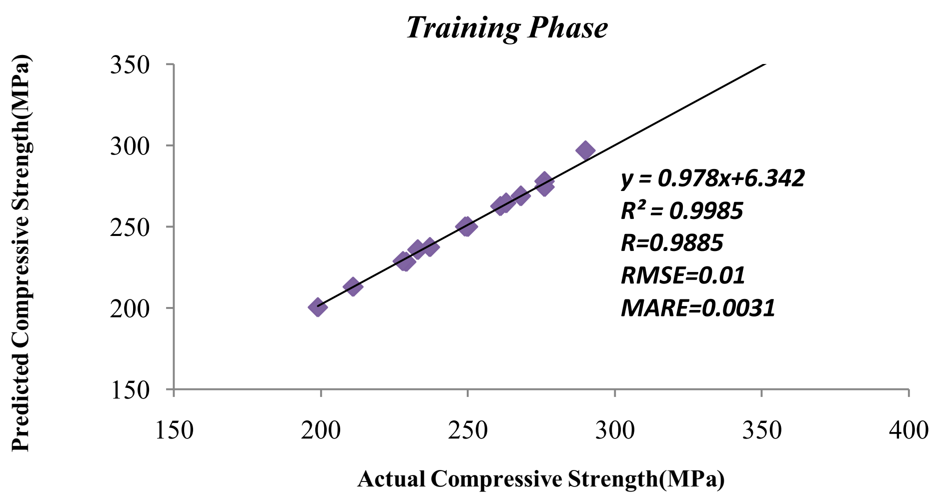

Fig.2 training Phase by ANN model

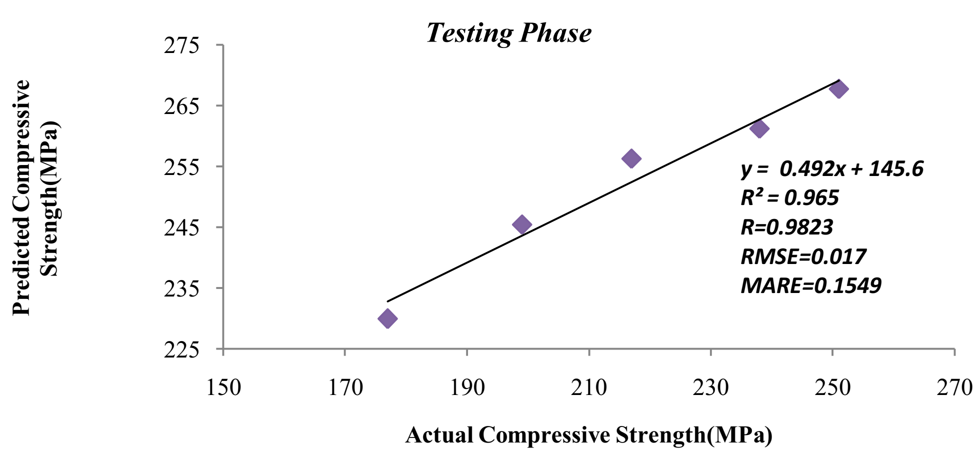

Fig.3 Testing Phase by ANN model

Fig 2 and 3 show all performance criteria and curve fitting in training and testing Phase .as it can be seen all these parameters in training phase are better than testing phase because of the large number of available data for training phase. All these parameter should be between [0, 1].

Generally, the optimal value for correlation coefficient and correlation of determination is 1 and in this model all effort was to obtain higher value for these factors.

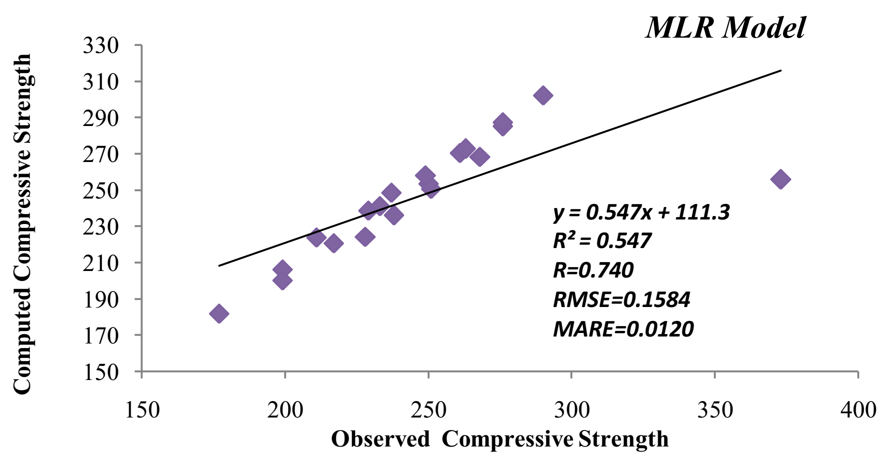

Fig.4 training Phase by MLR model

Traditional methods such as multi linear regression, also has been used in this study, Fig 4 shows fitting curve and performance criteria of this model. These factors show the low ability of MLR compare to ANN in prediction compressive strength Comparison between ANN and MLR prediction has been shown in fig 5. Better matching between observed compressive strength erosion and predicted data prove the high capability of ANN in prediction compare to MLR model .

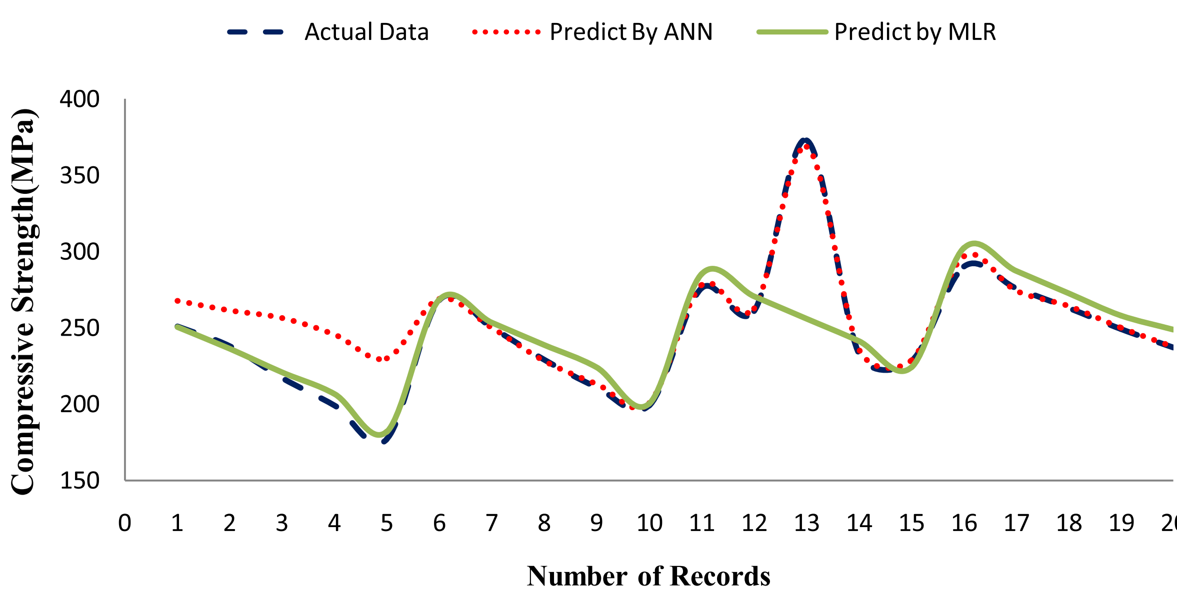

Fig.5 Comparison between ANN and MLR Prediction

Table.2 Comparison between ANN and MLR Prediction

	ANN		*MLR*
	Training	***Testing***	
RMSE	***0.01***	***0.017***	***0.1584***
R	***0.9885***	***0.9823***	***0.740***
R^2	***0.9980***	***0.9650***	***0.5478***
MARE	***0.0031***	***0.1549***	***0.0120***

All of performance criteria have been shown in Table2, as suggested by results MSE, RMSE and MARE is lower for ANN model, while the model has higher value in terms of correlation coefficient(R) and correlation of determination (R^2).

5 Conclusion

A back-propagation neural network has selected in order to assess feasibility of ANN's to predict the compressive strength of rubberized concrete. In order to develop and verify the model a database including 20 cases of recorded test measurement of rubberized concrete was complied.

The results indicate that back-propagation neural network have the ability to predict the strength of rubberized concrete with an acceptable degree of accuracy (R=0.982, RMSE=0.017). ANN method has an additional advantage over conventional method that is ones the model is trained , it can be used as an accurate and quick tool for estimating the compressive strength of any rubberized concrete.

The results of this study indicated that ANN's model produce more accurate tool for compressive strength prediction than those obtained via the traditional experiment methods.

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