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A Study on the Estimation of Prefabricated Glass Fiber Reinforced Concrete Panel Strength Values with an Artificial Neural Network Model

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Abstract: In this study, artificial neural networks trained with swarm based artificial bee colony optimization algorithm was implemented for prediction of the modulus of rapture values of the fabricated glass fiber reinforced concrete panels. For the application of the ANN models, 143 different four-point bending test results of glass fiber reinforced concrete mixes with the varied parameters of temperature, fiber content and slump values were introduced the artificial bee colony optimization and conventional back propagation algorithms. Training and the testing results of the corresponding models showed that artificial neural networks trained with the artificial bee colony optimization algorithm have remarkable potential for the prediction of modulus of rupture values and this method can be used as a preliminary decision criterion for quality check of the fabricated products.

Keywords: Neural network; glass fiber reinforced concrete; glass fiber.

1 Introduction

Concrete matrices supported with glass fibers are called glass fiber reinforced concretes (GFRC). These superior concrete are widely used in facade works, indoor and outdoor flooring and sculpturing works. The characteristics of GRFC are diversified depending on the fiber contents, densities and production environment temperatures. It is also known that, glass fibers enhance the mechanical properties of concrete including flexural strength, toughness, cracking and abrasion resistance.

In literature there are several studies which are investigating the influence of the GFRC and other additives on concrete. Mise, Mashima, and Yukawa (1982) investigated the mechanical properties of GRFC in the scope of structural utilization and they also reported that, compressive strength decreased due to the low shearing strengths of glass fibers. Fu, Lauke, Mäder, Yue, and Hu (2000) focused on the

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tensile strength characteristics of polypropylene composites reinforced with short glass fibers, and they observed that the tensile failure strain of the composites decreased with the increase of fiber volume fraction. Lv, Cheng, and Ma (2012) tested the glass fiber GFRC beam specimens with various fiber volume fractions under four-point flexural fatigue loading to obtain the fatigue-lives values for various stresses. The results pointed out that fatigue-life of GFRC fitted well with the two-parameter Weibull distribution. Kohno, Abe, Amo, and HORII (1985) worked on the utilization of condensed silica-fume in GFRC for quality improvements. Alhozaimy,Soroushian, and Mirza (1996) carried out an experiment regarding the influence of collated-fibrillated polypropylene fibers with low volume fractions on the compressive and flexural strength properties of concrete specimens with different binder compositions. Benmokrane, Chaallal, and Masmoudi (1996) performed an experimental and theoretical studies for comparing the flexural behaviors of concrete beams reinforced with fiber reinforced plastic reinforcing bars and, identical conventionally reinforced beams. Khaloo and Afshari (2005) investigated the influence of length and volumetric percentage of steel fibers on energy absorption of concrete slabs with various concrete strengths by testing steel fiber reinforced concrete slabs under flexure.

Artificial neural network (ANN) is an artificial intelligence method widely used in modeling complex nonlinear systems which are not easily modeled by using closed form equations. In literature, there exist many studies concerning the use of ANN for strength prediction. Ni and Wang (2000) proposed a method to predict 28-day compressive strength of concrete by using multi-layer feed-forward neural network. Kewalramani and Gupta (2006) conducted a study to predict the compressive strength of concrete based on their weights for two different concrete mixtures as a rapid test method for predicting long-term compressive strength of concrete. Shah, Shah, Samui, and Murthy (2014) focused on the prediction methods of fracture parameters of High strength and Ultra-High strength concrete elements by using minimax probability machine regression and extreme learning machines. Duan, Kou, and Poon (2013) stressed the applicability of ANN to predict the compressive strength of recycled aggregate concrete. Alshihri, Azmy, and El-Bisy (2009) implemented an ANN model to predict the compressive strength of light weight concrete mixtures after 3, 7, 14, and 28 days of curing. Yeh (1998) adapted the ANN to predict the compressive strength of high-performance concrete. Yuvaraj, Murthy, Iyer, Sekar, and Samui (2014) developed an ANN model to predict fracture characteristics of high strength and ultra-high strength concrete beams. In this study, ANN models were proposed for estimating the modulus of rupture (MOR) values of the concrete specimens reinforced with glass fibers.

2 Methodology

2.1 Artificial Neural Networks

ANN is a computational intelligent system developed for simulating the human brain functions. It comprises parallel processing elements (nodes or neurons) interconnected to each as biological neurons. In the ANN, nodes are connected to each other by synaptic weights similar to biological neurons. Despite the complexity of the brain, ANN is composed of nodes arranged in a limited number of layers to form the network architecture. Based on the characteristics of node connections, neural networks can be classified in many groups such as multilayer perceptron neural networks, wavelet neural networks and recurrent networks. Among them, in the scope of the multilayer perceptron neural networks the nodes in each layer are connected to the nodes of the next layer by interconnection weights and no loops are allowed through the model.

ANN modeling procedure consists of learning, validation and prediction steps. Modeling using ANN is initiated by introducing the learning data to the network. The information of training set is propagated from the input layer to the output by passing through the hidden layers. The connection weights and biases are modified by using the network error. The validation phase is used for testing the network generalization and stopping the training phase before the over fitting. In the prediction step, the trained model is ready for performing new predictions.

2.2 Back Propagation Algorithm

Among various learning algorithms, Back Propagation (BP) algorithm was developed by Rumelhart, Hinton, and Williams (1986) based on the steepest gradient descent principle and effectively used by Rojas (1996); Haykin (1998) on their researches. In this type of network, each node in a single layer connected to all the nodes of previous and next layer. The network is trained by altering the initially assigned weight values with progressive iteration cycles. The weight values are modified by comparing the network error and the known outputs. This error is back-propagated through the network to alter the synaptic weights. Within the scope of training step of the BP algorithm, the network output is compared with the real output, and the network error is propagated backward for altering the connection weights as per the method of ASCE Task Committee on Application of Artificial Neural Networks in Hydrology (2000).

A proper learning rate and momentum coefficient is used for an effective learning phase. Despite the fact that, a higher learning rate provides faster training phase, optimal weight values are required for establishing the best performing model. On the contrary, with a lower learning rate, ANN model has greater chance of being trapped in the local minima. According to the Rajasekaran and Pai's (2003) works, momentum term allows a change to the weights to persist for a number of adjustment cycles since it adds the influence of the past data points on the current movement of the weights. Extensive information about the neural networks and corresponding training algorithms can be found in Haykin's (1999); Zheng, Peng, and Hu (2014); Gresovnik, Kodejla, Vertnik, Sencic, Kovacic, and Sarler (2012) al. researches.

2.3 Multiple Linear Regression

Multiple linear regression (MLR) method proposes a regression model in which, the response or dependent variable Y is influenced by a set of m independent variable $X_1, X_2, \ldots X_m$. A linear relation between these variables can be identified as Eq. (1).

$$y = a + b_1 x_1 + b_2 x_2 + \cdots + b_m x_m \tag{1}$$

Regression analysis is a powerful and comprehensive tool for analyzing relationships between a dependent variables and independent variable. Generalized problem of the regression model includes the estimation of the model parameters and prediction independent variable with the dependent variables. Often, the model parameters or coefficients are predicted by using least square method. Montgomery, Peck, and Vining (2001) developed MLR and least square method on his detailed works.

2.4 ANN Training with ABC and BP Algorithms

A feed forward MLP network with BP algorithm was used in this study for prediction of MOR values. Basically a three-layer network with an input output and single hidden layer was selected. The input layer was composed of three neurons for slump value, fiber ratio and density. The optimum neuron number in the hidden layer was determined with trial and error procedure for 5, 10, 15 and 20 neurons. For the transfer function in hidden layer, tangent sigmoid was used.

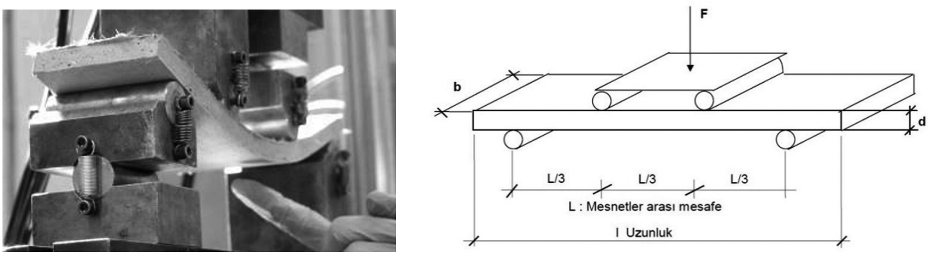
3 Experimental Phase

MOR values is known to depend on the beam size for glass fiber reinforced concrete specimens. Due to the fact that there is no large stable growth of a crack before the maximum load is reached, the size effect (unlike that in many other types of failure of concrete structures) cannot be explained by energy release due to fracture. This size effect must be explained by the fact that distributed micro-cracking and slips with strain softening take place in the boundary layer of the beam before the maximum load is reached. The beam is considered to fail before any macroscopic cracks are formed. In the scope of the study, a total of 144 tests were conducted. The properties of the specimens were carefully investigated and logged. These properties were summarized in Table 1.

Table 1: Characteristics of concrete mixture.

Type	Attribute
Cement	
SO_3 Content	2.87%
Cl Content	0.01%
Loss on Ignition	0.96%
Glass Fiber	
Approximate Length	14 mm
Specific Gravity	2.55
Water Solubility	Insoluble
Appearance	White
Aggregate	
Type	Natural, dry and clean
Nominal size	8 mm
Absorption Limit	1.2%
SiO_2Content	98.6%
Hyper Plasticizer	
Type	Carboxylic based
Dosage	1.5%
Density	1.055–1.085 kg/l
GRC specimen	
Cement content	754 kg
Sand content	834 kg
Water Amount	250 kg

Specimens were produced by mixing 750 kg cement, 834 kg sand and 250 kg water per one m^3 volume. Hyper-plasticizer amount kept constant as 1.5% of cement content in weight. Three rectangular prism specimens were molded in order to obtain 7 and 28-day flexural strength values. The latter, 28-day strength values were taken into account in the scope of this study. Four-point bending test was procedure was used for according to the EN1170 code as seen in Figure 1.



(a) (b)

Figure 1: (a) Ongoing EN1170 test and (b) sketch of the experiment setting.

4 ANN Model Development

The laboratory test results were taken into consideration as three candidate of input variables and a single output variable for ANN system. The corresponding input parameters are fiber ratio, density and slump value of the specimen and the output value is MOR value. The total of 144 test results were used for the study and 110 data-points were used for the training of the ANN, and 22 for testing of the model performances. For the ANN model, 15% of the training data set were excluded for validation step of the algorithm. The range of the model variables are seen in Table 2.

Table 2: Range of Model Variables.

Variables	Minimum	Maximum	Range
MOR	18.32	21.53	3.21
Fiber Ratio	3.65%	4.00%	0.45
Density	1952	2185	233
Slump	133	145	12

The linear relationships between the dependent and independent variables can be defined with the Pearson correlation coefficient; therefore, the cross-correlations were investigated for defining the dependencies among the variables as stated in Table 3.

As seen from Table 3, there was strong correlation between the independent and dependent variables. The correlation between the dependent variables were relatively low. Model structure was selected with a single hidden layer for the purpose of non-linear relationships can be mapped with a high degree of accuracy using a single hidden layer in parallel with Rumelhart, Hinton, and Williams (1986) works. Due to the reason that there is no any unified theory is available for determining the best ANN configuration, a trial-error procedure was selected for determining the

Table 3: Correlation Coefficients of Multiple Variables.

	Fiber Ratio	Density	Slump
Fiber Ratio			
Density	0.395		
Slump	0.682	0.306	
MOR	0.856	0.365	0.893

number of neurons in the hidden layer as per the studies of ASCE, Task Committee on Application of Artificial Neural Networks in Hydrology (2000). For this study, four neurons were used in the hidden layer and for each run cycle, these neurons were increased by four. The final ANN structure was concluded with three input variable for estimating the MOR value of the specimen as shown in Figure 2.

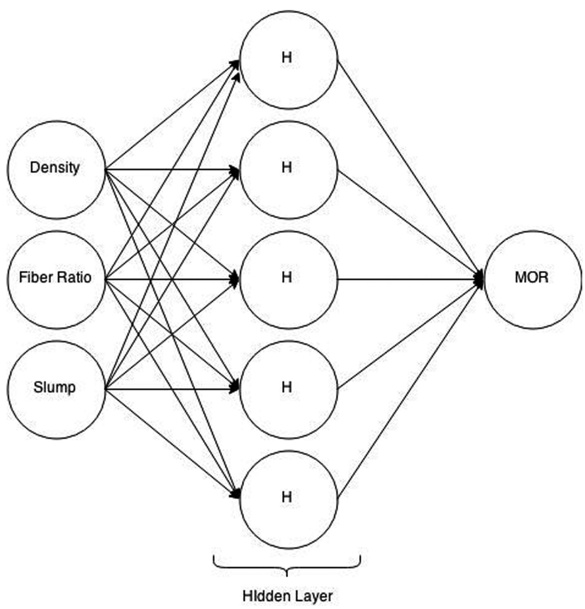


Figure 2: The proposed ANN structure.

For a reliable training process, a normalization procedure is recommended for the input signal for eliminating the bias of the network and improve network's prediction performance essential as Chandwani, Agrawal, and Nagar (2015) stated in their studies. Input and output values were normalized by implementing a standardization function shown as Eq. (2).

$$x_n = \frac{x_n - x_{\min}}{x_{\max} - x_{\min}} \tag{2}$$

where x_n, $x_{\max}$ and $x_{\min}$ represented the normalized data-set, maximum and minimum values in the dataset. Model performances were evaluated with mean square error (MSE) and correlation coefficient between the predicted and actual MOR values expressed as Eq. (3) which was derived by Lehmann and Casella (1998).

$$RMSE = \frac{1}{N}\sum_{i=1}^{N}\left(MOR_{obs} - MOR_{prd}\right)^2 \tag{3}$$

In Eq. (3), N is the number of data-points, MORobs is the experimental MOR values and MORprd is the predicted MOR values from the ANN model. Pearson's Correlation coefficient (R) measures the power correlation degree between the observed and model output can be described with Eq. (3).

$$R = \frac{\sum_{i=1}^{N}(T_i - \bar{T})\left(O_i - \bar{O}\right)}{\sqrt{\sum_{i=1}^{N}(T_i - \bar{T})^2 \sum_{i=1}^{N}\left(TO_i - \bar{O}\right)^2}} \tag{4}$$

where T_i and O_i are predicted value from the model and experimental values, $\bar{T}$ and $\bar{O}$ are mean predicted and experimental values and N is the total number of data-points. R statistic takes a value between 0 and 1 as the upper bound indicates a perfect correlation and lower bound indicates no correlation at all. R statistic is sensitive to the linearity between the variables and it may give non-approximate results in the case of available outliers. On the other hand, a lower MSE value indicates a more approximate model for the dataset. As both indices have pearls and pitfalls, the model performances were evaluated simultaneously using both MSE and R statistics.

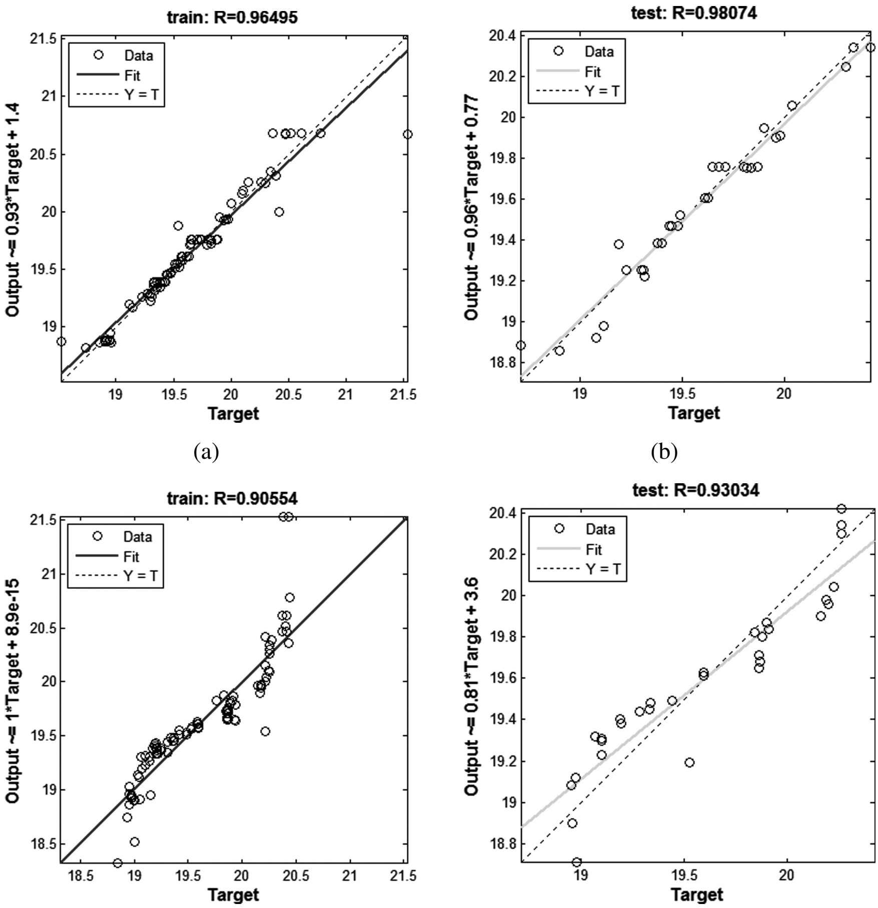
5 Results and Discussion

Both multiple linear regression and neural network models were prepared and executed in Matlab educational software. The accuracy of the ANN results were compared with MLR model. The model correlation coefficients and MSE values for five ANN models with different number of hidden neurons were shown in Table 4.

As seen in Table 4, the change in the number of neurons in the hidden layer can change the network performance comparing the R^2 and MSE values. The best performing ANN model was found as the first model with 5 neurons in the hidden layer. It was also found that both four ANN models were superior to the MLR model considering the R^2 and MLR values. ANN model performances were evaluated with the same epoch number of 7000. For each case, the epoch number was the stopping condition for eliminating over training of the network. With couple of trial and errors, and learning rate of 0.05 was found to be the optimum parameter parallel with the selected epoch number. The ANN-BP model with 5 neurons

Table 4: Performance Comparison of MLR model and ANN Models.

Num. of neurons in hidden layer	Training		Testing	
	R^2	MSE	R^2	MSE
5	0.964	0.0171	0.981	0.0059
10	0.955	0.0269	0.946	0.0185
15	0.952	0.0274	0.926	0.0239
20	0.958	0.0305	0.928	0.0217
MLR	0.905	0.0511	0.930	0.0273



(a) (b) (c) (d)

Figure 3: Regression plots for (a) training and (b) testing steps of the ANN and for (c) training and (d) testing steps of MLR model.

was selected as the best performing model and its regression plot was plotted with the MLR model to clarify the model performances as Figure 3 for the training and testing steps.

With examining the regression plots, it was concluded that, ANN models exhibit more fitting performance compared with the MLR model. Especially testing step of the MLR model overestimated the lower MOR values and relatively underestimated the high MOR values compared with the ANN model. In conclusion, analysis results show that, ANN models can be implemented for predicating the characteristics of the concrete specimens reinforced with fibers.

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