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A COMPREHENSIVE STUDY ON THE CONCRETE COMPRESSIVE STRENGTH ESTIMATION USING ARTIFICIAL NEURAL NETWORK AND ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM

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ABSTRACT

This research deals with the development and comparison of two data-driven models, i.e., Artificial Neural Network (ANN) and Adaptive Neuro-based Fuzzy Inference System (ANFIS) models for estimation of 28-day compressive strength of concrete for 160 different mix designs. These various mix designs are constructed based on seven different parameters, i.e., 3/4 mm sand, 3/8 mm sand, cement content, maximum size of aggregate, gravel content, water-cement ratio, and fineness modulus. In this study, it is found that the ANN model is an efficient model for prediction of compressive strength of concrete. In addition, ANFIS model is a suitable model for the same estimation purposes, however, the ANN model is recognized to be more fitting than ANFIS model in predicting the 28-day compressive strength of concrete.

Keywords: concrete; compressive strength; ANFIS; ANN.

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1. INTRODUCTION

Concrete is one of the most fundamental construction materials which is broadly utilized for the construction purposes. Concrete compressive strength is considered as one of the most important properties of concrete which clearly demonstrates its level of quality assurance

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[1]. Developing accurate and trustworthy models for estimating the concrete compressive strength would lead to saving both costs and time. In this regard, many scientists have conducted researches in order to estimate the compressive strength of concrete using data-driven models [2, 3, 4, 5, 6].

Data-driven models are widely used for prediction purposes in civil engineering field. Kaveh and Servati (2001) have used the backpropagation neural networks for design of double layer grid. They have claimed that these trained networks can strongly be utilized in such design procedure within the bounds being considered [7]. Kaveh and Dehkordi (2003) have developed the efficient neural networks for all the three steps of analysis, design, and estimation of the domes' displacements using both the Backpropagation and Radial Basis Functions neural networks [8]. Rofooei et al. (2011) have applied different artificial neural networks in order to predict the vulnerability of any typical reinforced MRF concrete structures [9]. Sadowski et al. (2015) estimated the pull-off adhesion between concrete layers using principal component analysis combined with a self-organization feature map and found this method capable for prediction purposes [10]. Khademi and Behfarnia (2016) have used both the Artificial Neural Network (ANN) and Multiple Linear Regression (MLR) models to determine the compressive strength of concrete. They have concluded that the ANN model is a suitable model in predicting the compressive strength of concrete, however the MLR is better to be used for preliminary concrete mix designs [3]. In this paper, two prediction techniques, i.e., Artificial Neural Network (ANN) and Adaptive Neuro-based Fuzzy Inference System (NFIS) are developed in MATLAB software [11] in order to predict the 28-day compressive strength of concrete specimens (f_{c28}) and the results of both models are compared with each other.

2. DATA COLLECTION AND MATERIAL PROPERTIES

Various concrete specimens were constructed under laboratory condition with respect to 7 different mix parameters, i.e., 3/4 mm sand, 3/8 mm sand, cement content, maximum size of aggregate (MSA), gravel content, water-cement ratio (w/c), and fineness modulus of aggregates (FM), shown in Table 1. All specimens were cured for 28 days and in order to reach the objective of this research, total of 160 records of concrete mix designs were chosen [4, 12]. It is worth mentioning that all the specimens were 150 mm by 300 mm cylindrical specimens.

Table 1: Characteristics of Concrete Mix Parameters

Number	**Parameters**	**Unit**	**Maximum**	**Minimum**
1	f_{c28}	MPa	39.40	17.30
2	w/c	_	0.50	0.24
3	MSA	mm	50.00	5.12
4	Gravel content	Kg	1050.00	559.00
5	Cement content	Kg	549.00	243.00
6	Sand 3/8	Kg	523.00	303.00
7	Sand 3/4	Kg	693.00	365.00
8	FM	_	9.20	2.40

3. PREDICTION TECHNIQUES

Recently, scientists have developed different soft computing techniques to estimate specific parameters, compressive strength of concrete, as an example. It is worth mentioning that these methods are capable enough to be replaced instead of traditional and time consuming measuring methods. In this study, Artificial Neural Network (ANN) and Adaptive Neuro-based Fuzzy Inference System (NFIS) models are developed to estimate the 28-day compressive strength of concrete which are explained shortly in the following.

3.1 Artificial neural network (ANN)

Artificial Neural Network (ANN) is an information processing model derived from the learning ability of human brain. It is a data-driven model involving an input layer, one or more hidden layer(s), and an output layer. The hidden layer is attached to the other layers using biases, weights, and transfer functions [3, 4]. The difference between network output and the target would lead to determination of an error function. The error is propagated back and both the biases and weights are fixed using specific optimization methods which minimizes the error. The whole process called Training step, goes over of several epochs to get to the most accuracy in outputs. The validation step which comes after the Training step, is used indirectly while the ANN is trained to monitor the over-fitting of the neural network. It stops the training of ANN when the error of the Validation step begins to increase. The final step of the ANN modeling is called Test step which evaluates the accuracy of the machine learning algorithm [3, 13, 14, 15, 16]. In this paper, for ANN model, 70% of the total data were selected for Training step, 15% for Validation step, and 15% for Test step.

3.2. Adaptive neuro-fuzzy inference system

Adaptive Neuro-Fuzzy Inference System (ANFIS) is a universal estimator which was first developed by Jang [17]. It incorporates the human-like reasoning style of fuzzy inference system through the use of input-output sets and a linguistic model consisting of a set of IF_THEN fuzzy rules [18]. ANFIS is comprised of five different layers including input, input membership function, rule, output membership function, and output [18, 19]. The backpropagation gradient descent is considered as the primary rule of ANFIS. It determines the error signals recursively from the output layer backward to the input nodes. This learning rule and the one which is used in the general feed-forward neural networks are almost identical to each other [18, 19]. Recently, ANFIS has adapted hybrid-learning method which is a quick learning method for its predicting purposes. The hybrid algorithm has been recognized as a precise algorithm by many scientists [19, 20]. In this research, same as ANN model, in application of ANFIS model 70% of the total data were selected for Training step, 15% for Validation step, and 15% for Test step.

4. RESULTS AND DISCUSSION

In order to estimate the 28-day concrete compressive strength, 160 different concrete mix specimens were selected in this research. Following, two different prediction models, i.e. Artificial Neural Network (ANN) and Adaptive Neuro-based Fuzzy Inference System (ANFIS) models were selected to predict the compressive strength of concrete. Both the ANN and ANFIS models were constructed in MATLAB software [11]. In addition, the data were categorized into three sets of training, validation, and test and the 28-day compressive strength of concrete was predicted based on these three subsets. Finally, the performance of both of the models were compared with each other using the coefficient of determination (R^2), shown in Eq. (1) [6].

$$R^2 = \frac{[\sum_{i=1}^{n}(y_i - \bar{y})(\hat{y}_i - \bar{\hat{y}})]^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2 \sum_{i=1}^{n}(\hat{y}_i - \bar{\hat{y}})^2} \tag{1}$$

where “y_i" is the experimental strength of "i"$^{\text{th}}$ specimen, "$\bar{y}$" is the averaged experimental strength, “$\hat{y}_i$” is the calculated compressive strength of "i"$^{\text{th}}$ specimen, and "$\bar{\hat{y}}$" is the averaged calculated compressive strength.

4.1 Artificial neural network

Seven different input variables i.e. 3/4 mm sand, 3/8 mm sand, cement content, maximum size of aggregate, gravel content, water-cement ratio, and fineness modulus were selected as the input variables for ANN modeling. In addition, the 28-day compressive strength of concrete was chosen as the only output variable. Furthermore, the total of 160 different concrete specimens were selected for modeling purposes in which among all of them 70% (i.e. 112 specimens) were picked for training step, 15% (i.e. 24 specimens) were picked for validation (check) step, and 15% (i.e. 24 specimens) were picked for test step.

Different algorithms for the training of artificial neural network are established by scientists which some of them are Momentum, Levenberg Marquardt, Quickprop algorithms. All these algorithms are tried in this research, and among all of them, the Levenberg Marquardt (LM) algorithm was chosen as the most efficient one. In addition, the number of hidden layers was chosen as 15, based on the formula presented in Eq. (2) [4].

$$N_H \leq 2N_1 + 1 \tag{2}$$

where N_H is the maximum number of nodes in the hidden layer and N_1 is the number of inputs. In this research, the ANN model was created in MATLAB environment and Figs. 1, 2, and 3 are extracted from this software [11]. Fig. 1 presents the Mean Squared Error (MSE) of ANN model for training, validation (check), and test steps. According to this figure, the least MSE in the validation step is happened at epoch 3 which has the best validation performance equal to 239.6299. It is worth mentioning that model training keeps going as long as the error of the network on the validation vector is reducing. In addition, the analysis stop point is equal to 9, i.e. 6 error repetitions after the epoch with the best validation performance, i.e. epoch 3.

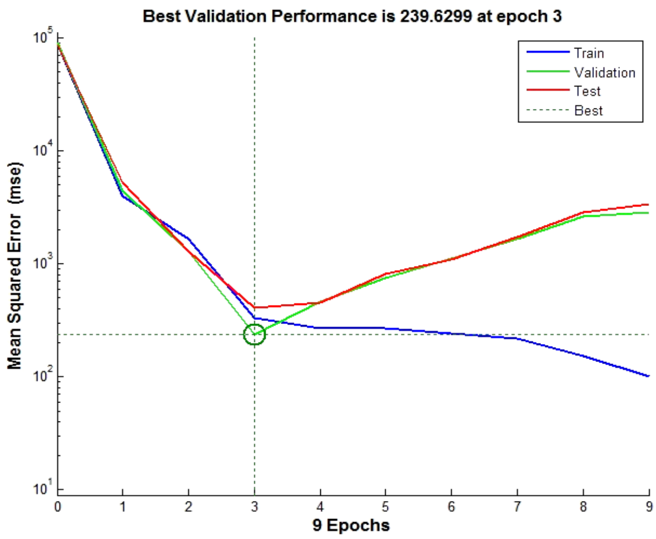

Figure 1. Best validation performance in artificial neural network

Fig. 2 presents the training state of ANN model. According to this Figure, the last epoch before the error repetitions, i.e. epoch 3 has the best validation performance, and therefore, the model final weights are picked based on the weights of this epoch. Based on this Figure, as it was also mentioned previously, the number of error repetitions is equal to 6 which would lead to having the validation check of equal to 6. This Figure also illustrated that the network processing is stopped at epoch 9, i.e. 6 epochs after the epoch with the best validation performance.

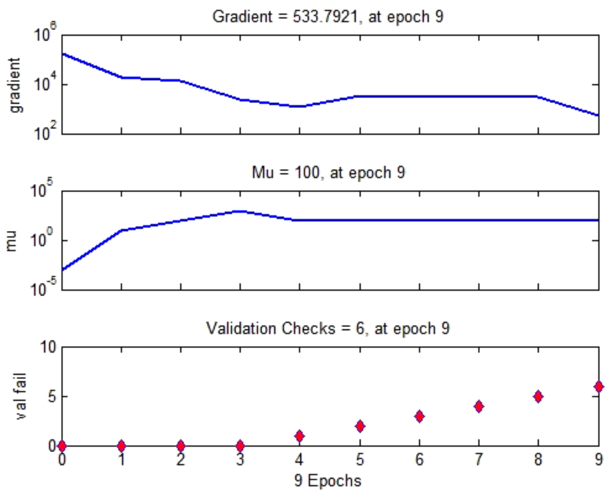

Figure 2. Training state of ANN model

Fig. 3 shows the correlation between the target (measured 28-day compressive strength) and output (estimated 28-day compressive strength) values for both the training and validation, created in MATLAB software. According to this Figure, both the training and validation show desirable correlation coefficients (R values). The correlation coefficient shows how strong the association between two variables are.

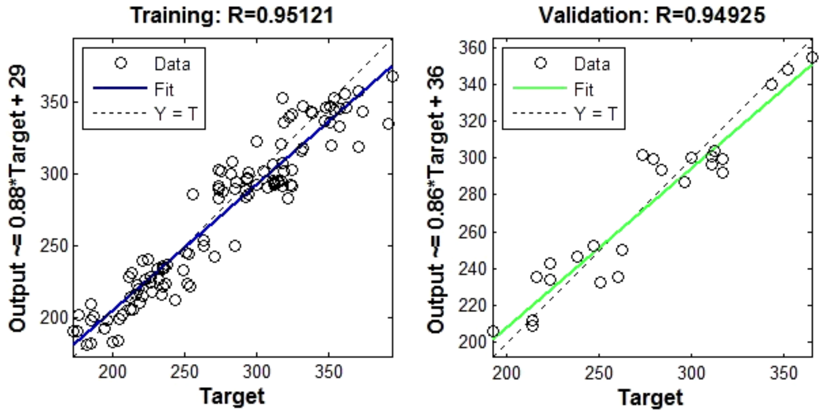

Figure 3. Regression of training and validation subsets in ANN model

4.2 Adaptive neuro-fuzzy inference system

In this research, ANFIS model was applied using MATLAB environment [11]. The total of 160 different concrete specimens were selected for ANFIS modeling which among all of them 70% (i.e. 112 specimens) were selected for training step, 15% (i.e. 24 specimens) were selected for validation (check) step, and 15% (i.e. 24 specimens) were selected for test step. Figs. 4 and 5 are resulted from this software modeling. Fig. 4 presents the target (blue nodes) and output (red nodes) data for 112 selected specimens of the training step. According to this Figure, there is a good correlation between the target and output data with the error percentage of 11.1020 which shows the efficient ANFIS modeling.

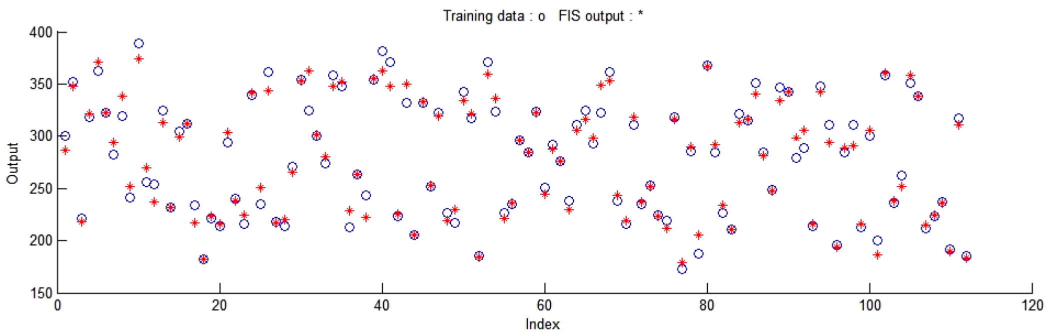

Figure 4. Comparison between the “Target” and “Output” parameters for “Training” data in ANFIS model

In addition, according to Fig. 5, there is a good coincidence between the target and output values for the selected 24 specimens of validation step in ANFIS model. Same as Fig. 4, target and output values are shown by blue and red colors, respectively.

Figure 5. Comparison between the “Target” and “Output” Parameters for “Validation” data in ANFIS model

4.3 Comparison of results of ANN and ANFIS models

Figs. 6 and 7 show the performance of estimation of compressive strength of concrete for test data for ANN and ANFIS models, respectively. According to these Figures, both models are found to be capable in predicting the concrete compressive strength of concrete in terms of R^2 values. In addition, comparing the R^2 values of the both of the models, it can be concluded that ANN with the coefficient of determination of R^2= 0.9321 is more efficient than ANFIS model with the coefficient of determination of R^2= 0.8931 in terms of estimating the compressive strength of concrete.

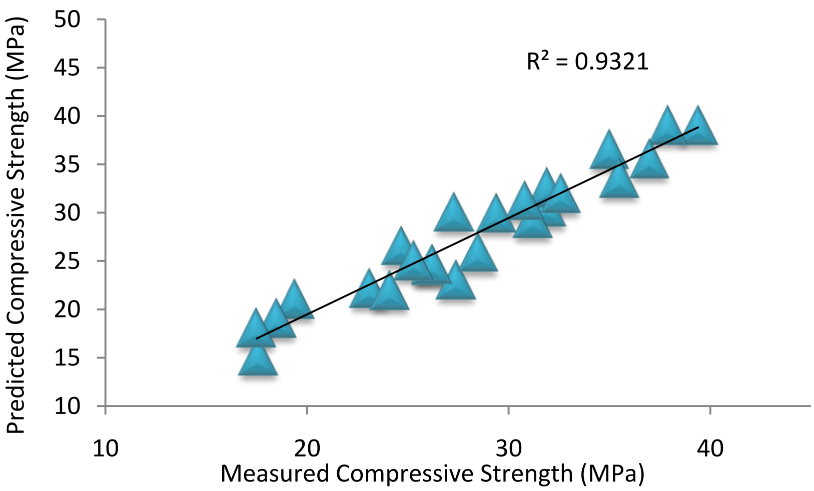

Figure 6. Comparison between the “Measured” and “Predicted” parameters for “Test” data in ANN model

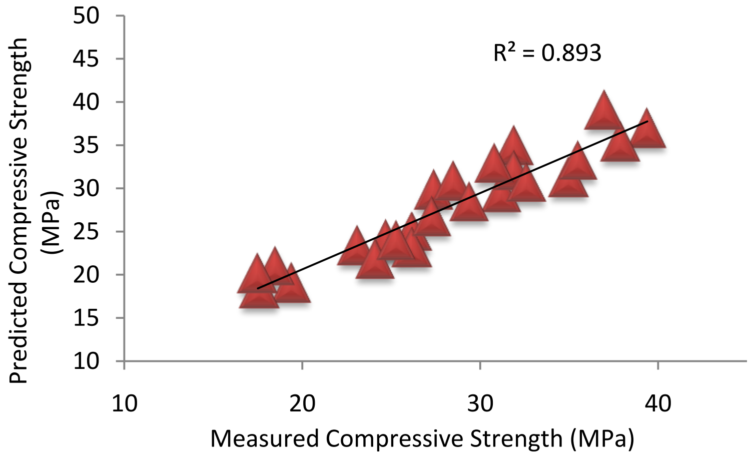

Figure 7. Comparison between the "Measured" and "Predicted" parameters for "Test" data in ANFIS model

5. CONCLUSION

In the present study, two data-driven models, i.e., Artificial Neural Network (ANN) and Adaptive Neuro-based Fuzzy Inference System (NFIS) were developed for estimating the 28-day compressive strength of concrete based on 7 different concrete parameters i.e., 3/4 mm sand, 3/8 mm sand, cement content, maximum size of aggregate, gravel content, water-cement ratio, and fineness modulus of aggregates. The following conclusions can be drawn from this research study:

1) It is concluded that the ANN model with the R^2 value of equal to 0.9321 can strongly predict the 28 days compressive strength of concrete.
2) Results have shown that ANFIS model with the R^2 value of equal to 0.8930 is capable enough in estimating the 28 days compressive strength of concrete.
3) The results obtained from the ANN and ANFIS demonstrated a high degree of coherency with the experimental results. Therefore, both the ANN and ANFIS models were found to be efficient in predicting the 28-day compressive strength of concrete.
4) Although the ANFIS model was proved to be suitable in estimating the compressive strength of concrete, the ANN model is recognized to be more capable than ANFIS model for the same predicting purposes.

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