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# Application of ANN and ANFIS Models in Determining Compressive Strength of Concrete

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## ABSTRACT

Concrete compressive strength is recognized as one of the most important mechanical properties of concrete and one of the most significant mechanical properties in determining the quality of the produced concrete. Since the traditional procedures of determining the compressive strength of concrete require time and cost, scholars have always been looking for new methods to replace them with existing traditional methods. In this paper, soft computing methods are investigated for determining the compressive strength of concrete. To be specific, 150 different concrete specimens with various mix design parameters have been built in the laboratory, and the compressive strength of them have been measured after 28 days of curing in the water. Five different concrete mix parameters, (i.e., cement, water to cement ratio, gravel, sand, and microsilica) were considered as input variables. In addition, two soft computing techniques have been used in this study which are Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference (ANFIS) System. Results have shown that both of ANN and ANFIS models are successful models for predicting the compressive strength of concrete. Also, results have shown that ANFIS is more capable than ANN in predicting the compressive strength of concrete.

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# 1. Introduction

Nowadays, the use of soft computing techniques by different researchers is increased. Soft computing techniques, also known as data-driven models, are models based on the computational modeling and work based on input-output data. Using these methods would result in saving a significant amount of time and cost, besides the accuracy of these models. Among all, Artificial Neural Network (ANN) and Adaptive Neuro-Fuzzy Inference System (ANFIS) are used in multiple occasions by scientists. The ANN technique is composed of multiple nodes which imitates biological neurons in the human brain. The neurons connect to each other through links. The ANFIS is a kind of Artificial Neural Network that is based on Takagi-Sugeno fuzzy inference system.

Scientists have utilized the ANFIS and ANN models in the different area of science successfully. Krishna et al. have successfully used ANN and ANFIS in studying the fluidized bed with internals [1]. Hamdia et al. have effectively used these two models in predicting the fracture toughness of PNCs [2]. Naderpour et al. developed a new approach to obtain the FRP-confined compressive strength of concrete using a large number of experimental data by applying artificial neural networks [3]. Khademi et al. have used the ANN and ANFIS models efficiently in determining the displacement in concrete reinforcement buildings [4]. Gupta et al. have skillfully used these models in estimating the performance of a plate-fin heat exchanger by exploration [5]. Talebizadeh and Moridnejad have performed the uncertainty analysis on the forecast of lake level fluctuations [6]. Khademi et al. have estimated the 28-days compressive strength of concrete through ANN and ANFIS models [7]. Zemgyi Ma et al. have used these models to classify the heating value of burning municipal solid waste in circulating fluidized bed incinerators [8]. Güneyisi et al. have successfully predicted the flexural over strength factor for steel beams using artificial neural network [9]. Nasrollahi has skillfully predicted the optimum shape of large-span trusses according to AISC-LRFD using Ranked Particles Optimization [10]. The statements above were examples of the application of successfully used different soft computing methods for predicting various civil engineering characteristics. Keshavarz provided a summary of the literature in which the civil engineering characteristics were predicted through soft computing models [11].

This study aims to investigate the capability of Artificial Neural Network and Adaptive Neuro-Fuzzy Inference system in evaluating the compressive strength of concrete. In this paper, 150 concrete mix designs were constructed in the laboratory based on five different mix parameters (i.e., cement, water to cement ratio, gravel, sand, and microsilica) and after 28 days of curing the concrete in water, the compressive strength of each was evaluated. Next, two different soft computing techniques (i.e., Artificial Neural Network and Adaptive Neuro-Fuzzy Inference System) were modeled in MATLAB© 2013. In the modeling, the concrete mix parameters were used as input variables and the compressive strength of concrete were used as an output parameter. Subsequently, obtaining the results, the outcomes of these two models are developed and compared with each other. The flowchart of this study is shown in Figure 1.

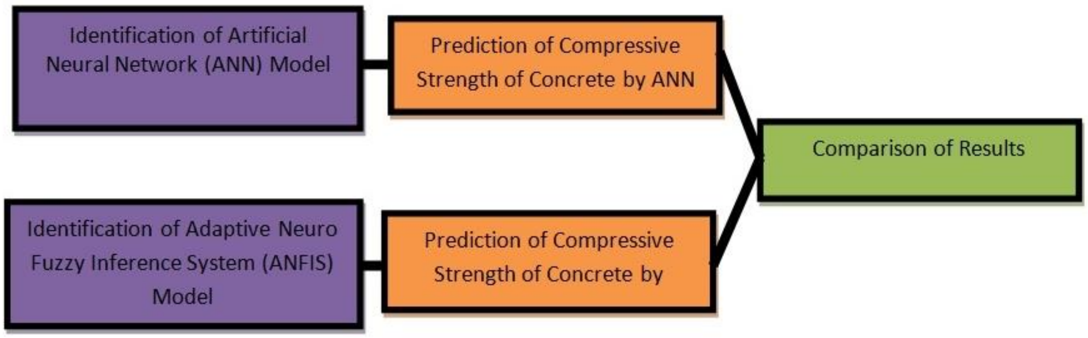


**Fig. 1.** Flow chart of this Study.

## 2. Data preparation and methods

In order to get to the objective of this study, various concrete specimens were made in the laboratory and cured in water for 28 days. In overall, 150 different concrete specimens were constructed in the laboratory. The concrete specimens were made in a cylindrical shape with the diameter of 150 mm and height of 300 mm. The input parameters influencing the compressive strength of concrete were cement, gravel, sand, microsilica, and water to cement ratio. The characteristics of these data are shown in Table 1.

**Table 1**
Characteristics of Input Parameters.

| Input Parameter | Range |
|---|---|
| **Cement (Kg)** | 230- 548 |
| **Water (Kg/m3)** | 90-260 |
| **Grave (Kg)** | 538- 1039 |
| **Sand (Kg)** | 301- 656 |
| **Microsilica (Kg/m$^3$)** | 10- 60 |

In the next step, the Artificial Neural Network and Adaptive Neuro-Fuzzy Inference System models were selected as estimation models of predicting the 28 days compressive strength of concrete. In both of the models, the data were divided into three subcategories of training, validation, and test. Both the modeling have been performed in MATLAB© 2013. Finally, the performance of the ANN and ANFIS models were compared with each other based on the defined dataset. The performance Criteria for comparing the results of this study is determined based on the coefficient of determination ($R^2$), shown in EQ (1).

$$R^2 = \frac{[\sum_{i=1}^{n}\left(y_i - y_i'\right)\left(y_i'' - y_i'''\right)]^2}{\sum_{i=1}^{n}\left(y_i - y_i'\right)^2 \sum_{i=1}^{n}\left(y_i'' - y_i'''\right)^2} \tag{1}$$

Where $y_i$ is the experimental strength of i$^{th}$ sample, $y_i'$ is the averaged experimental strength, $y_i''$ is the determined compressive strength of the ith sample, and $y_i'''$ is the averaged determined compressive strength.

## 3. Artificial neural network

Artificial neural networks are famous as data processing systems which include the artificial neurons. These artificial neurons are a vast number of simple, highly incorporated processing elements inspired by the complex structure of the brain. For the purpose of improving their performance, these neurons have the ability to learn from the experiences. The artificial neural network can be identified as a network comprised several processors which are called neurons (also known as units). Each neuron includes a numerical data which could be known as weights [12,13].

In order to build a useful neural network, 3 steps should be considered: (1) Selection of an appropriate architecture for the artificial neural network, (2) using sufficient training data for creating the network, and (3) Using different test data groups to test the accuracy of the network. Figure 2 shows the architecture of an artificial neural network model [13,14].

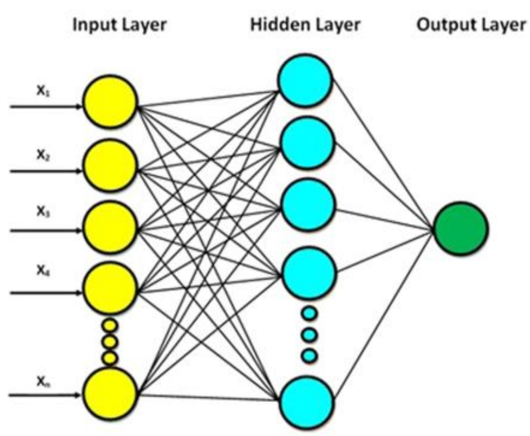


**Fig. 2.** The architecture of the Artificial Neural Network (adapted from [10]).

The connection strength is estimated through weighted connections. These weights are trained to make the output variables as close as possible to target values. ANN is consist of three different steps of train, validation, and test. The training step goal is to minimize the error function. In the validation step, the artificial neural network is used to construct the model, and it works independently from the training step. The test step is used to anticipate the accuracy of the machine algorithm [14].

Neural networks are categorized into layers. The input layer and output layers are consist of input data and the resulting output data. Between the input and output layers, the hidden layer exists which includes neurons and are connected by the weights, which are explained earlier. There might be any number of hidden layers, and the two-layer network may map any number of non-linear relationship. Each layer is a vector containing any number of R of neurons, and the output of the layer is a vector of length R containing the output from each neuron in that layer. This output vector is next passed as the input vector for the next hidden layer, and this specific process continues for all hidden layers till the final output of the network is reached [15,16].

The concrete specimens that are studied in this research have the compressive strength of between 200 $Kg/m^3$ to 350 $Kg/m^3$. The total of 150 specimens has been studied in this research. In order to have the better understanding of the concrete specimens used in this study, the number of specimens in each interval are presented in Table 2.

**Table 2**
Number of Specimens in Each Interval.

| Interval of Concrete Compressive Strength ($Kg/m^3$) | Number of Specimens in each Interval |
|---|---|
| **150-200** | 39 |
| **200 to 250** | 28 |
| **250 to 300** | 32 |
| **300 to 350** | 51 |

In this study, these total of 150 data is divided into three categorizations of train, validation, and test, for the ANN modeling. This categorization is shown in Table 3.

**Table 3**
Categorization of Studied Data in ANN Modeling.

| Step | Percentage | Number of Specimens |
|---|---|---|
| **Train** | 60% | 90 |
| **Validation** | 10% | 15 |
| **Test** | 30% | 45 |
| **Total** | 100% | 150 |

Different algorithms were ran in this study to find the best-fitted model, and among all, the Levenberg- Marquardt (LM) was chosen. The results of the test step for the ANN modeling of these specimens are shown in Figure 3. This Figure demonstrates the relationship between the measured and estimated compressive strength of concrete.

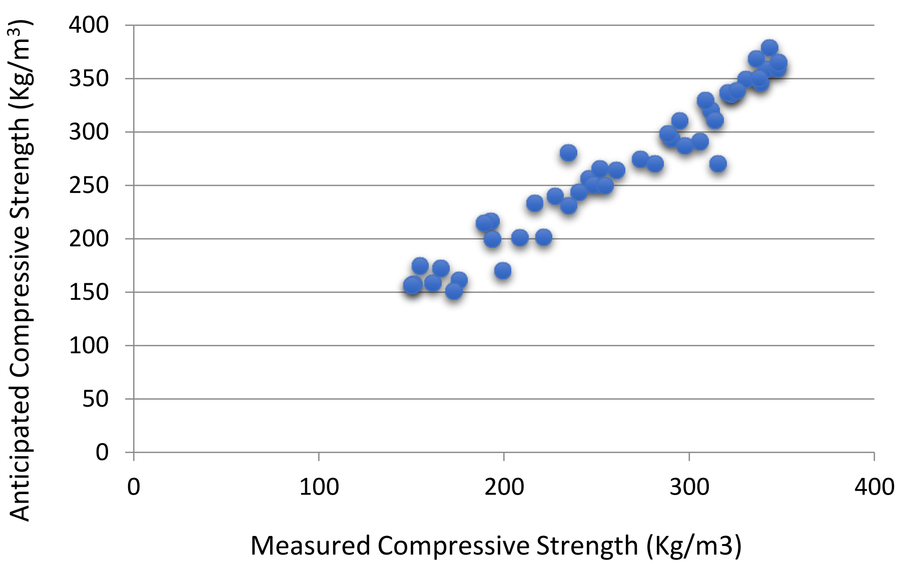


**Fig. 3.** Comparison of Measured and Anticipated Data for the Test Step of ANN Model.

According to this Figure, the $R^2$ coefficient for ANN modeling of the test data is equal to 0.942. This number confirms that the ANN model is a suitable model in predicting the compressive strength of concrete.

## 4. Adaptive neuro-fuzzy inference system

Adaptive Neuro-Fuzzy Inference System also known as ANFIS incorporates the self- learning ability of neural networks with the linguistic expression function of fuzzy inference. In order to train the Takagi- Sugeno type fuzzy inference system which would result in a search for the optimal elements, ANFIS combines the least squares and backpropagation gradient. In other words, ANFIS is a multilayer feed-forward network in which each node performs a particular function on receiving signals and has a set of parameters pertaining to this node. Similar to ANN, ANFIS is capable of unseen mapping inputs to their outputs by learning the rules from previously observed data. The architecture of ANFIS is shown in Figure 4 [4,17,18].

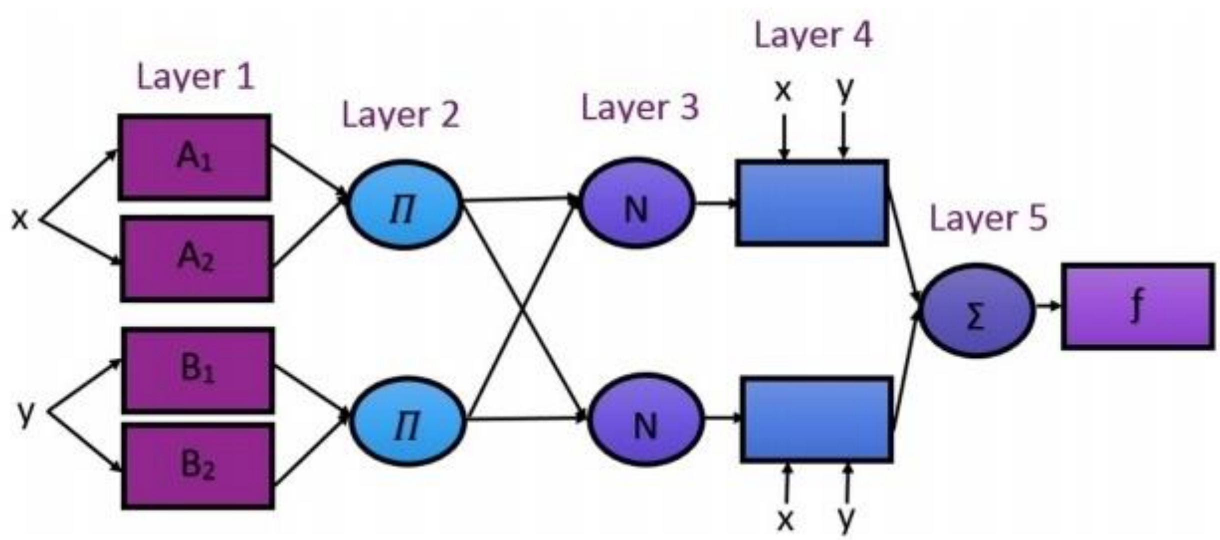


**Fig. 4.** The architecture of ANFIS Model (Adapted from [4]).

The ANFIS model includes 5 different layers. Each layer includes different nodes described by the node function. Layer one is the layer in which all the nodes are adaptive nodes with a node function. Layer two is the layer in which node multiplies incoming signals, and the output is the product of all the incoming signals. Layer 3 calculates the ratio of the $i^{th}$ rules firing strength to the sum of all rule's firing strength of the nodes. In layer 4, each node calculates the contribution of the $i^{th}$ rule to the overall output. In layer 5, the signal node calculates the final output as the summation of all input signals [4,17–21].

The ANFIS model is divided into three steps of train, check, and train. The portion of data used in each step in ANFIS modeling is shown in Table 4.

**Table 4**
Categorization of Studied Data in ANFIS Modeling.

| Step | Percentage | Number of Specimens |
|---|---|---|
| **Train** | 60% | 90 |
| **Check** | 10% | 15 |
| **Test** | 30% | 45 |
| **Total** | 100% | 150 |

The results of the test step for the ANFIS modeling of these specimens are shown in Figure 5. This Figure shows the correlation between the measured and estimated compressive strength of concrete.

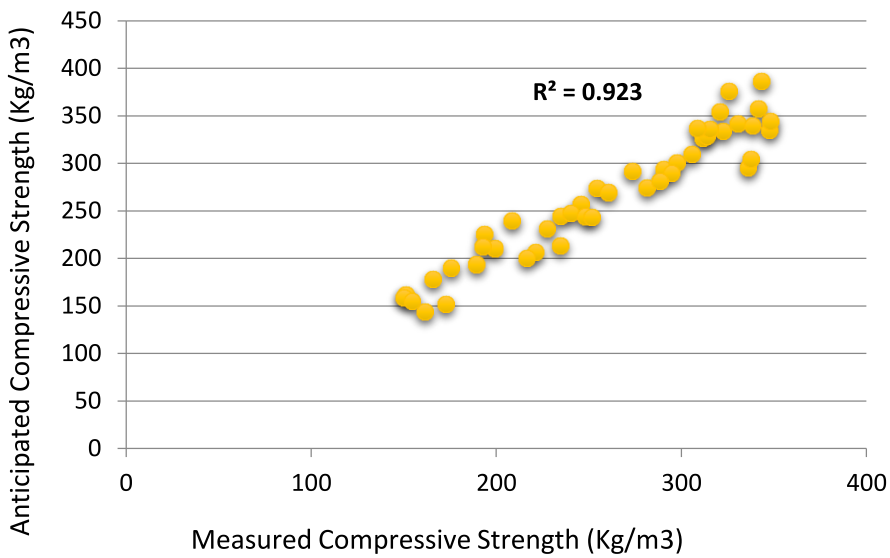


**Fig. 5.** Comparison of Measured and Anticipated Data for the Test Step of ANFIS Model.

According to Figure 5, the $R^2$ coefficient for ANFIS modeling of the test data is equal to 0.923. This number confirms that the ANFIS model is a suitable model in predicting the compressive strength of concrete.

## 5. Comparison of ANN and ANFIs

In order to better illustrate the efficiency of ANFIS and ANN models, there is the need to compare their results with each other. One of the well-known factors that could be used in such prediction comparisons is the coefficient of determination, defined in EQ (1). The coefficient of determination is simply a statistic that gives some information about the goodness of fit of a model. In other words, it is a statistical measure of how well the model predicts the actual data points. The higher coefficient of determination indicates that the model better fits the data. The $R^2$ coefficient for both of the models is shown in Table 5.

**Table 5**
The $R^2$ coefficient for ANN and ANFIS Models

| Model | $R^2$ Value |
|---|---|
| **ANN** | 0.942 |
| **ANFIS** | 0.923 |

Based on what explained before, the higher values of coefficient of determination would indicate the better capability of the model in predicting the specific studied characteristics. According to this table, the $R^2$ value for the ANN model is equal to 0.942 which shows the capability of this model in estimating the compressive strength of concrete. In addition, the $R^2$ value is determined as 0.923 for the ANIFIS model which demonstrates the fact that this model is a skillful model in predicting the compressive strength of concrete. To overall, the $R^2$ value for both the ANN and ANFIS models are high, and therefore, both of the models are skillful ones in predicting the compressive strength of concrete. In addition, a comparison of these two models shows that the $R^2$ value of the ANN model is higher than the one for the ANFIS model. As a result, the ANN model is a more capable model than ANFIS in predicting the compressive strength of concrete.

## 6. Conclusion

This study is a comprehensive study on the performance of soft computing models in predicting the concrete compressive strength. In this study, two soft computing models of ANN and ANFIS were used to estimate this characteristic of concrete. The result show that ANN and ANFIS models are both successful models in determining the compressive strength of concrete. Also, the comparison of ANN and ANFIS models showed that the ANN model is more accurate than ANFIS in predicting the compressive strength of concrete.

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