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# AN ARTIFICIAL INTELLIGENCE APPROACH FOR CONCRETE HARDENED PROPERTY ESTIMATION

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**Abstract**

An alternative method using Artificial Intelligence (AI) to predict the 28-day strength of concrete from its primary ingredients is presented in this research. A series of 424 data samples collected from a previous study were employed for developing, testing, and validation of Adaptive Neuro-Fuzzy Inference System (ANFIS) models. Seven mix parameters, namely Cement, Blast Furnace Slag, Fly Ash, Water, Superplasticizer, Coarse Aggregate, and Fine Aggregate were used as the inputs of the models while the output was the 28-day compressive strength of concrete. In the first step, different models with various input membership functions were explored and compared to obtain an optimal ANFIS model. In the second step, that model was utilized to predict the compressive strength value for each concrete sample, and to compare with those obtained from the compressive test in laboratory. The results showed that the selected ANFIS model can be used as a reliable tool for predicting the compressive strength of concrete with Root Mean Squared Error values of 5.97 MPa and 7.73 MPa, respectively, for the training and test sets. In addition, the sensitivity analysis results revealed that the accuracy of the proposed model improved with an increase in the number of input parameters/variables.

*Keywords:* artificial intelligence; adaptive neuro-fuzzy inference system; concrete strength; sensitivity analysis.

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## 1. Introduction

Concrete and reinforced concrete are commonly used as building construction materials all over the world. In the United States, reinforced concrete is a dominant structural material in engineered construction [1]. The reinforced concrete is widely used for many structures such as skyscrapers, as well as for the large infrastructures, including bridges, superhighways, and dams. Concrete is a mixture of cement, aggregate, and water. A proper concrete mixture requires workability for fresh concrete and durability and strength for the hardened stage. Small coarse aggregate sizes are often used for the relatively thin buildings, and the larger aggregates, up to 15 cm in diameter, are utilized for large dam structures [2]. Water is needed for the chemical reaction to form a cement paste and offers workability for fresh concrete. Typical components of a concrete mixture are depicted in Fig. 1.

Among many concrete characteristics, compression strength is usually considered the most valuable hardened property of concrete. It is measured by breaking cylindrical concrete specimens in a compression-testing machine at 28 days of standard curing. The testing procedure and standard size of

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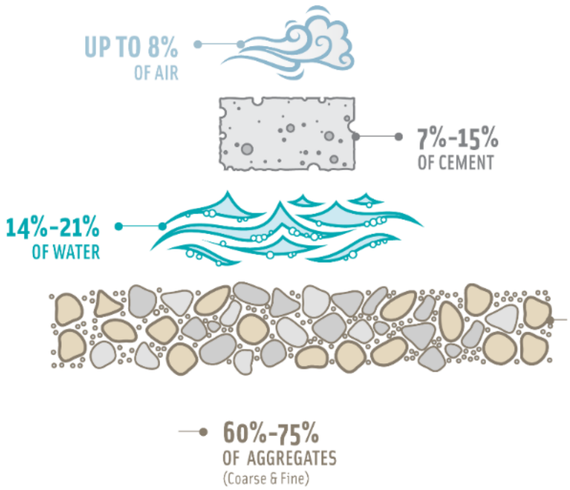



Figure 1. Components of concrete [2]

test specimens are in accordance with American Society for Testing and Materials (ASTM) C39 [3]. To obtain the average strength of concrete, the strength test results of at least two specimens are often required [4]. Several factors might affect the concrete compressive strength such as age, ingredients, water to cement ratio, curing conditions, etc. Typically, the compression test result of concrete at 28 days is considered as a standard to determine the quality of concrete.

If the compression test result does not meet the required strength, the mix design needs to be replaced, which might be labor-intensive and time-consuming. To minimize the risk of a specific concrete mix design falling short of compression strength requirement at the age of 28 days, a method to predict the 28-day strength from its primary ingredients is essential. Traditionally, the experimental method is broadly used to study the properties of materials [5–8]. In recent years, the application of the artificial intelligence-based models such as ANFIS and Artificial Neural Networks (ANN) to predict the concrete mechanical properties has increased significantly. Those models have an ability to learn from the data to establish the non-linear relationship between the inputs and outputs for the complex engineering issues.

Many researchers have used ANFIS model to predict the 28-day compressive strength of different concrete types. In their research, the number of the inputs, the number of membership functions, and the input ingredients were varied from one to another depending on the available experimental data. For example, Khademi et al. [9] used 173 concrete mix designs to develop, train, and test ANFIS models. Seven input parameters and one output were selected in such models. The coefficient of determination was used to evaluate the performance of the proposed model. The results from that study indicated that the ANFIS model could be used for predicting the 28-day concrete compressive strength. The application of the ANFIS model was also presented in the work for high-performance concrete [10–12], no-slump concrete [13], and for determining the Bridge Deck Corrosiveness Index [14].

Another AI-based model, ANN model, is also popular among researchers to estimate the compressive strength of concrete. For instance, Duan et al., [15] applied the ANN method for recycled aggregate concrete. In that study, an ANN model with 14 input parameters was trained and tested with 146 data points. Three indicators, namely Root Mean Squared Error, Absolute Fraction of Variation, and Mean Absolute Percentage Error, were used for the ANN model evaluation. The study concluded that the ANN had a fair accuracy in predicting the strength of recycled aggregate concrete. Additionally, the ANN model was employed for the prediction of compressive strength of other concrete types, including light-weight concrete [16, 17], and self-compacting concrete [18–20].

Besides the applications for estimating the compressive strength of various types of concrete material, the ANFIS and ANN approach have also been utilized by many researchers to deal with the various engineering problems. As an example, Bingöl et al., [21] applied the ANN approach to study the effects of the high temperature on the light-weight compression strength. The results from Bingöl's study revealed that the ANN model successfully predicted the nonlinear behavior of the concrete compressive strength after high-temperature effects. Other researchers applied the ANN model to estimate the slump of concrete [22, 23], to determine the ultimate load factor of nonlinear inelastic steel truss [24], to forecast the air quality [25], to predict the bridge desk rating [26], or to optimize the performance in the wastewater treatment plant [27].

In this study, a supervised learning ANFIS model was developed to predict the compressive strength of concrete at 28 days. Data used in training and testing model were collected from a previous study [28]. The ANFIS structure was developed in MATLAB R2019a Runtime Environment with seven input parameters and one output. The performance of various ANFIS models using different membership functions was evaluated to determine the optimal model for the experimental data. In addition, the proposed ANFIS model was used to study the sensitivity of the number of inputs to the model performance.

## 2. Data preparation

The original data contained the compressive strength of concrete at different ages. Since the current study aimed to predict the 28-day compressive strength concrete using the data-driven method, only the concrete test samples with 28-day compressive strength were extracted from the original dataset. The data after refinements were stored in a table format of 424 rows and 8 columns. Each row in the table included both input and output information of each test sample. The input parameters were stored from column one to column seven, and the output parameter was archived in the last column.

Table 1. Characteristics of input and output

| No. | Input | | | | | | | Output |
|---|---|---|---|---|---|---|---|---|
| | CEM (kg/m$^3$) | BFS (kg/m$^3$) | FLA (kg/m$^3$) | WTR (kg/m$^3$) | SPP (kg/m$^3$) | COA (kg/m$^3$) | FIA (kg/m$^3$) | F28 (MPa) |
| 1 | 540 | 0 | 0 | 162 | 2.5 | 1055 | 676 | 62 |
| 2 | 380 | 95 | 0 | 228 | 0 | 932 | 594 | 36 |
| 3 | 266 | 114 | 0 | 228 | 0 | 932 | 670 | 46 |
| - | - | - | - | - | - | - | - | - |
| - | - | - | - | - | - | - | - | - |
| 422 | 148.5 | 139.4 | 108.6 | 192.7 | 6.1 | 892.4 | 780 | 24 |
| 423 | 159.1 | 186.7 | 0 | 175.6 | 11.3 | 989.6 | 788.9 | 33 |
| 424 | 260.9 | 100.5 | 78.3 | 200.6 | 8.6 | 864.5 | 761.5 | 32 |
| Min. | 102 | 0 | 0 | 122 | 0 | 801 | 594 | 9 |
| Max. | 540 | 359 | 200 | 247 | 32 | 1145 | 993 | 82 |

Table 2. Number of samples in each specific range of 28 days compressive strength

| No. | 28-day compressive strength (MPa) | Number of samples |
|---|---|---|
| 1 | 0 - 15 | 17 |
| 2 | 15 - 30 | 129 |
| 3 | 30 - 45 | 181 |
| 4 | 45 - 60 | 61 |
| 5 | 60 - 75 | 33 |
| 6 | 75 - 90 | 3 |
| Total | | 424 |

Seven concrete ingredients namely Cement (CEM), Blast Furnace Slag (BFS), Fly Ash (FLA), Water (WTR), Superplasticizer (SPP), Coarse Aggregate (COA), and Fine Aggregate (FIA) were used as the inputs of the model. The model output was the 28-day compressive strength of concrete (F28). The range of the input and output parameters is shown in Table 1. The classification of the 28-day compression strength of concrete in each specific interval is presented in Table 2.

## 3. Adaptive Neuro-Fuzzy Inference System

The Adaptive Neuro-Fuzzy Inference System uses Neural Network learning method to fine-tune the Fuzzy Inference System parameters. The basic ANFIS architecture with two input variables is illustrated in Fig. 2. In this architecture, two fuzzy IF-THEN rules based on a first-order Sugeno model are presented

$$\text{Rule 1: IF } x \text{ is } A_1 \text{ AND } y \text{ is } B_1, \text{THEN } f_1 = p_1 x + q_1 y + r_1.$$
$$\text{Rule 2: IF } x \text{ is } A_2 \text{ AND } y \text{ is } B_2, \text{THEN } f_2 = p_2 x + q_2 y + r_2.$$

where $x$ and $y$ are the inputs; $A_i$ and $B_i$ are the fuzzy sets; $f_i$ are the outputs within the fuzzy region specified by the fuzzy rule; $p_i, q_i$, and $r_i$ are the design parameters that are determined during the training process.

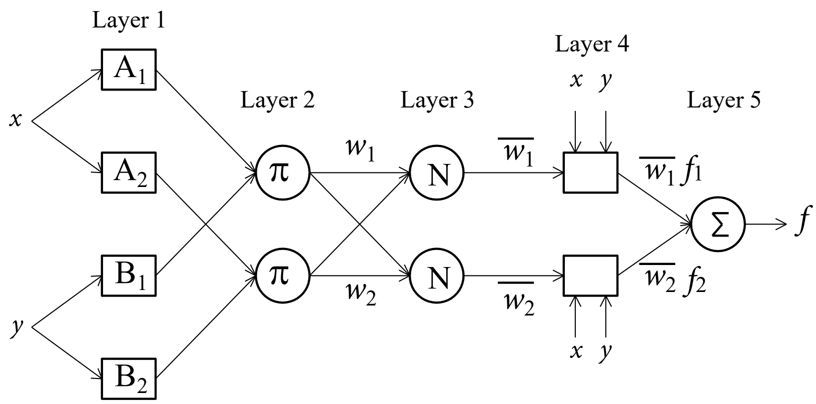



Figure 2. Structure of the ANFIS model

As shown in Fig. 2, the ANFIS model includes 5 layers with the fixed nodes depicts as circles. The details of each layer are identified in the following [4].

(i) Layer 1 consists of all adaptive nodes and the outputs are the fuzzy membership grade of the inputs, as given by Eq. (1)

$$O_{1,i} = \mu_{A_i}(x) \tag{1}$$

where $x$ is the inputs to node $i$, and $A_i$ is the linguistic labels associated with this node function.

(ii) Layer 2 involves fuzzy operator that related to the firing strength of the rules. The output of this layer is given by

$$O_{2,i} = w_i = \mu_{A_i}(x) \times \mu_{B_i}(y), \quad y = 1, 2 \tag{2}$$

(iii) Layer 3 is related to the normalization of the firing strength for each node in this layer using Eq. (3). The output from this layer is normalized firing strengths.

$$O_{3,i} = \overline{w}_l = \frac{w_i}{w_1 + w_2}, \quad y = 1, 2 \tag{3}$$

(iv) Layer 4 involves in the production between the normalized strength at each node with a first-order polynomial. For the Sugeno model, the output of this layer is calculated as

$$O_{4,i} = \overline{w}_l \times f_i = \overline{\omega}_l \left(p_i x + q_i y + r_i\right), \quad y = 1, 2 \tag{4}$$

where $\overline{w}_l$ is the output of Layer 3, and $p_i, q_i$, and $r_i$ are the design parameters.

(v) Layer 5 includes the summation of all input signals to produce a single output

$$O_{5,i} = \sum_i w \times f_i = \frac{\sum_i w_i \times f_i}{\sum_i w_i} \tag{5}$$

### *3.1. Model construction*

The ANFIS model was used to predict the compressive strength of concrete at 28 days (F28). Inputs for the model were seven parameters of concrete, namely CEM, BFS, FLA, WTR, SPP, COA, and FIA. Data set used for the ANFIS model was randomly divided into two subsets in which the training data subset contains about 85% of the entire data, i.e., 360 data samples and a testing data subset accounts for 15% of the entire data, i.e., 64 data samples. The structure of the ANFIS model is depicted in Fig. 3. For simplicity, only some connections are presented in the figure. Both hybrid and backpropagation optimal methods with different epoch numbers were tested for optimum performance. To generate the initial ANFIS model, different number and type of input membership functions were examined to obtain the optimum solution.

Both the linear and constant membership function was used for the output. For each combination, the performance of the ANFIS model was evaluated by calculating the RMSE for both training and testing data set. Table 3 presents details of several combinations and the average performance error for both training and testing data. An ANFIS model was selected based on the optimum performance and time of computing of all models in the combinations. The selected ANFIS model consisted of two 'gaussmf' input membership functions and one 'linearmf' output membership function. The optimal backpropagation method was chosen with an epoch number of 100. More detailed information about the selected ANFIS model is listed in Table 4.

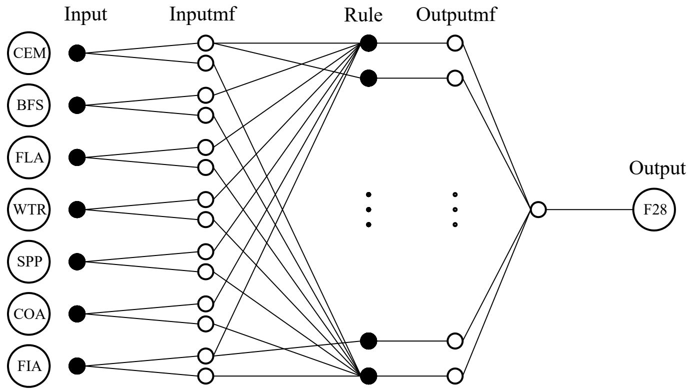



Figure 3. Structure of the ANFIS model

Table 3. Average performance error of some selected combinations

| Input membership function | Output membership function | Number epochs | RMSE | |
|---|---|---|---|---|
| | | | Training data | Testing data |
| trimf | linearmf | 100 | 5.80 | 7.85 |
| trapmf | | | 6.32 | 7.97 |
| gbellmf | | | 6.12 | 7.66 |
| gaussmf | | | 5.97 | 7.73 |
| gauss2mf | | | 6.32 | 7.99 |
| pimf | | | 6.57 | 8.23 |
| dsigmf | | | 6.21 | 7.35 |
| psigmf | | | 6.21 | 7.35 |

Table 4. Structure of the ANFIS model

| Information | Value |
|---|---|
| Number of nodes | 294 |
| Number of nonlinear parameters | 1024 |
| Number of nonlinear parameters | 42 |
| Total number of parameters | 1066 |
| Number of training data pairs | 360 |
| Number of fuzzy rules | 128 |

### *3.2. Model assessment*

The root mean squared error indicator (RMSE) was used to evaluate the performance of the model. RMSE is the root of the average squared difference between predicted outputs and actual outputs. RMSE can be calculated using Eq. (6)

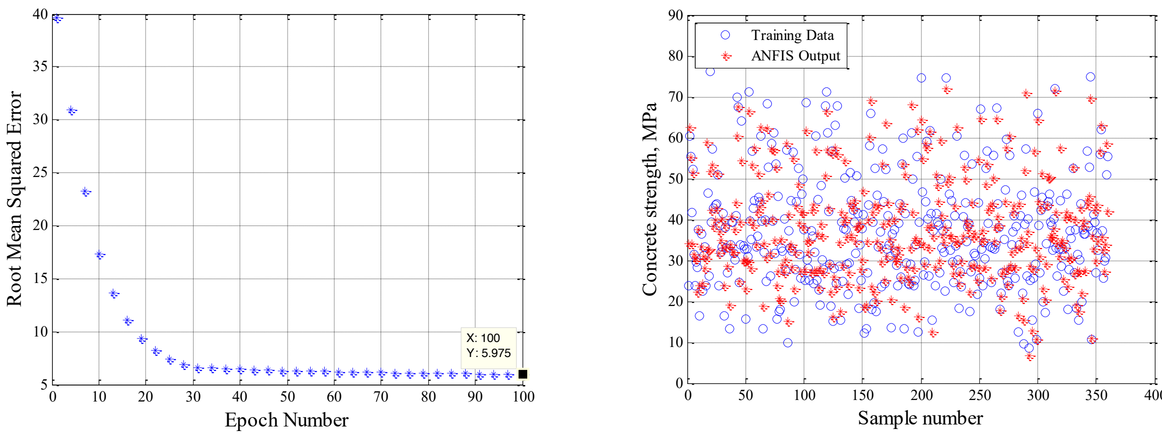
$$RMSE = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(y_i - \hat{y}_i)^2} \tag{6}$$

where $y_i$ is the $i^{th}$ actual output; $y_i$ is the $i^{th}$ predicted outputs; $n$ is the total number of samples.

It is worth mentioning that the lower the value of RMSE is, the better the model would be. The value of the error size depends on several factors, including the quantity and type of input membership functions, types of output membership functions, optimization methods, and the number of epochs/iterations. By adjusting these factors, the effective ANFIS model with the minimum error size can be achieved.

## 4. Results and discussion

Fig. 4 shows the results of the training the selected ANFIS model. The values of RMSE were decreased significantly in the first 30 epochs and reached the minimum value of 5.97 MPa at an iteration of 100, as shown in Fig. 4(a). The comparison of the concrete compressive strength of 360 samples in the testing data with the compressive strength of the test samples predicted from the ANFIS model is shown in Fig. 4(b).



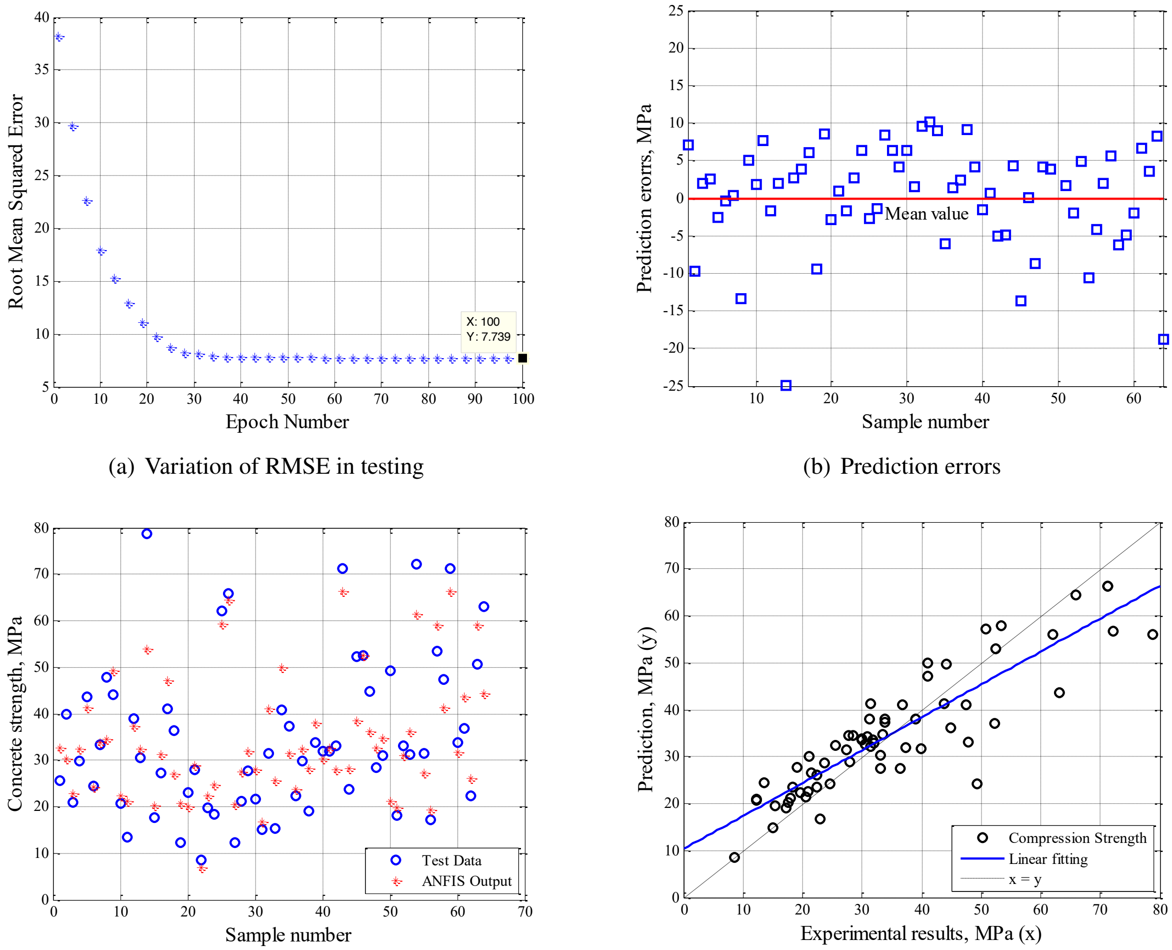

(a) Variation of RMSE in training

(b) Original vs prediction value

Figure 4. ANFIS model in training

In order to evaluate the performance of the proposed ANFIS model, the trained model was tested with the unseen data in the test set. It worth noting again that the test set contained 64 samples, which were randomly selected from the original data and not included in the training set. The performance of the ANFIS model for the data test set are presented in Fig. 5.

As can be seen in Fig. 5(a), the ANFIS model performed well on the data test set with the value of RMSE was 7.73 MPa. Fig. 5(b) presents the prediction errors of the entire test set using the proposed model. The prediction errors were calculated by subtracting the compression strength of concrete samples in the experimental test data with the sample compressive strength predicted by the ANFIS model. For the most test samples, the prediction error of the proposed model varied within an acceptable range of ±5 MPa. Some specimens experienced a huge difference between the predictions and experimental data. The reason for the unexpected results might be due to the inherent nature of the experimental data. As listed in Table 2, the original data contained very few test samples with the compression strength lower than 15 MPa or higher than 75 MPa. Thus, insufficient general characteristics from limited samples would result in the poor performance of the model.




(a) Variation of RMSE in testing

(b) Prediction errors

(c) Original vs prediction value

(d) Linear regression

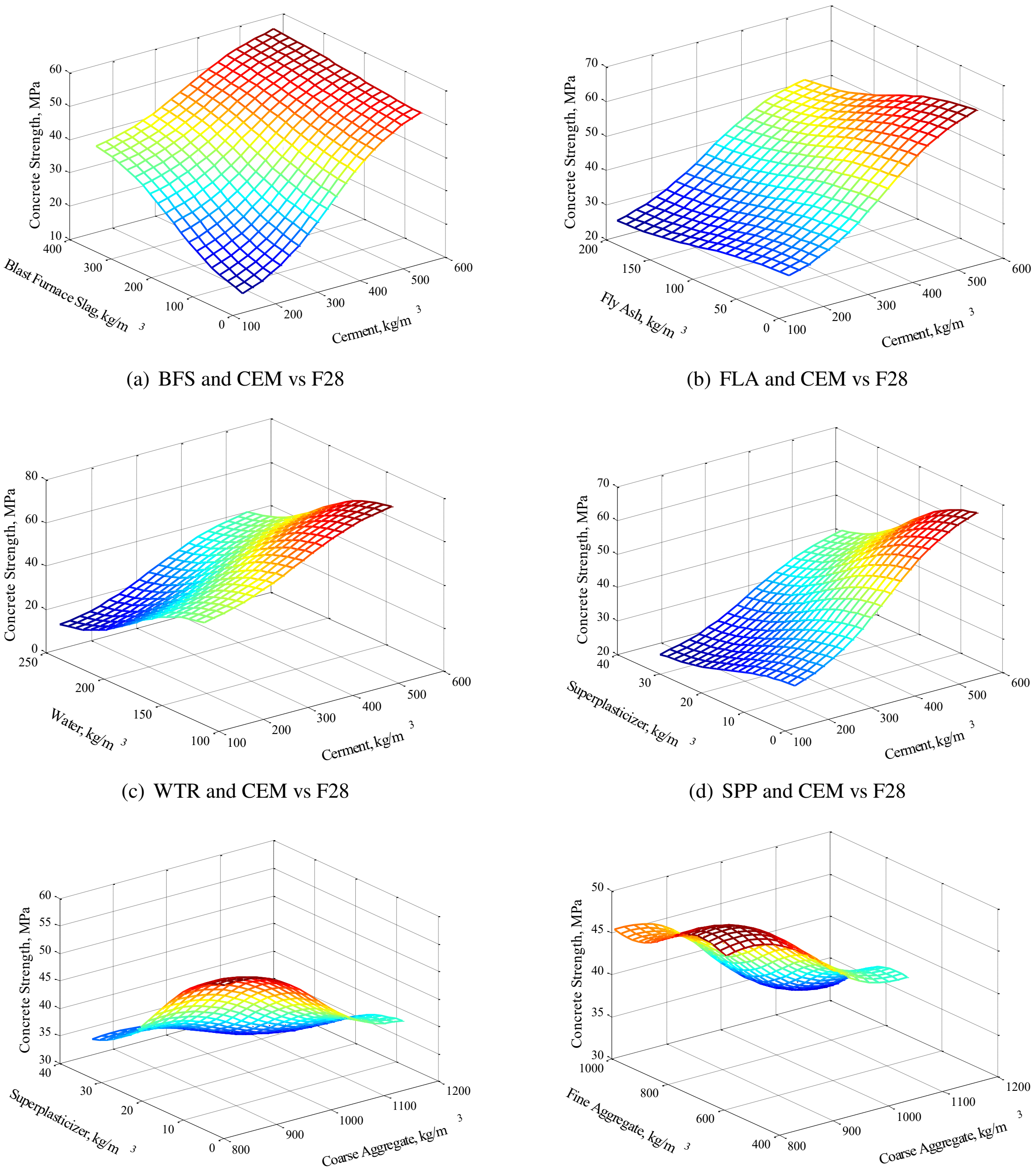
Figure 5. Performance of ANFIS model

Figs. 5(c) and 5(d) show the visualization of the performance of the ANFIS model for the test data. While in Fig. 5(c), the compressive concrete strength from experimental data and the value predicted by the model were comparable for each sample, the regression plot in Fig. 5(d) provided the visualization of the proposed ANFIS model performance. In the figure, the horizontal axis represents the experimental data of the test samples, and the vertical axis represents the predictions. The data samples with the compression strength values positioned on the diagonal line presented the coincident between experimental data and prediction values.

### *4.1. Inputs and output relationship*

The ANFIS model was also used to establish the relationship between the inputs and the output. Fig. 6 shows the three-dimensional (3D) surface diagram of the relationship between different input parameters and the 28-day concrete compression strength. The relationships between some major selected input ingredients and the output of the ANFIS model are presented in Fig. 7.

As can be seen from Fig. 6, the connection between cement and other inputs such as Blast Furnace




(a) BFS and CEM vs F28

(b) FLA and CEM vs F28

(c) WTR and CEM vs F28

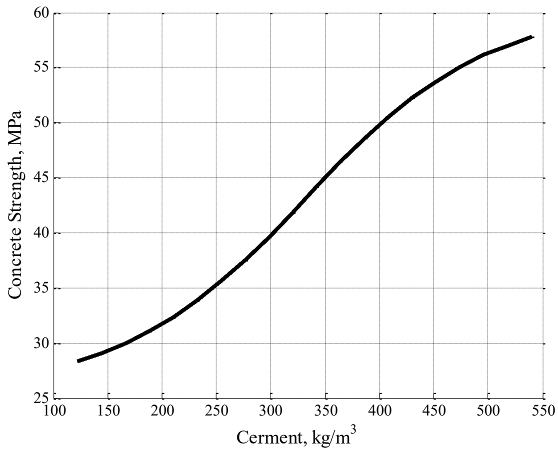
(d) SPP and CEM vs F28

(e) SPP and COA vs F28

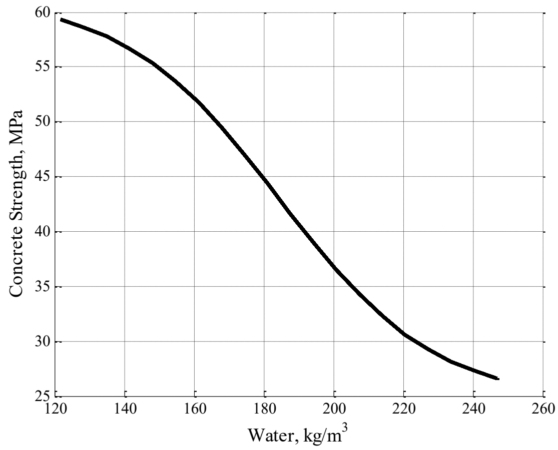
(f) FIA and COA vs F28

Figure 6. Surface diagram for the relationship between different inputs and output

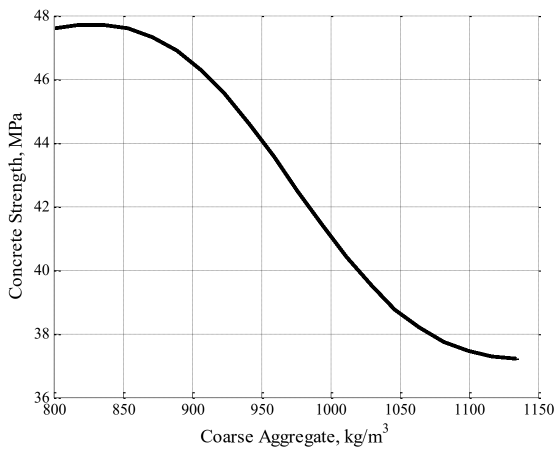
Slag (Fig. 6(a)), Fly Ash (Fig. 6(b)), Water (Fig. 6(c)), and Superplasticizer (Fig. 6(d)) to the 28-day concrete compression strength was almost linear. However, the strong non-linear relationship was found between the Coarse Aggregate and other inputs to the output, as presented in Figs.6(e) and 6(f). This non-linear relationship was also observed clearly in the two-dimensional plot in the following section.



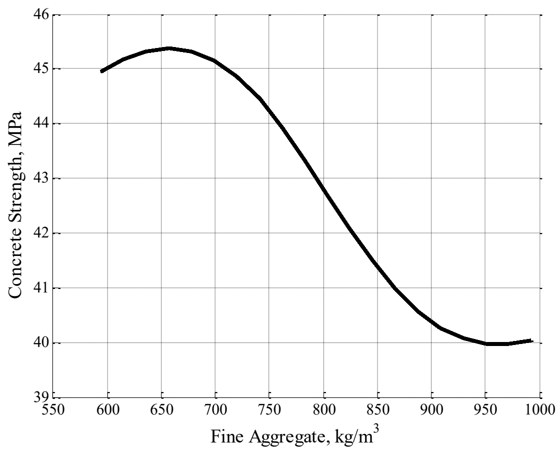

(a) F28 vs CEM




(b) F28 vs WTR




(c) F28 vs COA




(d) F28 vs FIA

Figure 7. Two-dimensional plot for the relationship between different inputs and output

Within the context of this study, data from the two-dimensional plot in Fig. 7(a) indicated that the concrete compressive strength at 28 days increased along with a rise in the amount of cement in the mixture. The reversed trend was found true for the amount of water in the concrete mixture, as shown in Fig. 7(b). With respect to the amount of coarse and fine aggregate, the 28-day compressive strength of the concrete specimens decreased when the amount of coarse and fine aggregate increased, as presented in Figs. 7(c) and 7(d). The 28-day concrete compressive strength was reached the maximum when the concrete mixture contained approximately 830 kg/m$^3$ and 670 kg/m$^3$ for coarse and fine aggregate, respectively.

## 4.2. Number of input analysis

The number of input analysis was also evaluated in this study using the ANFIS model. To do that, a basic ANFIS0 model was constructed using four mandatory concrete input ingredients, namely (i) Cement (CEM), (ii), Water (WTR), (iii) Coarse Aggregate (COA), and (iv) Fine Aggregate (FIA). In order to conduct the sensitivity analysis on the number of inputs, different models were developed by adding the input parameter into the basic model. A variable of BSF was added into the ANFIS0 to create an ANFIS1 model. Similarly, an ANFIS2 model was created by adding FLA to the ANFIS1 model, and a parameter SPP was added to the ANFIS2 model to construct an ANFIS3 model. It is worth noting that the new variable was added to the ANFIS model without considering the order of the parameters. Detailed of these models are listed in Table 5.

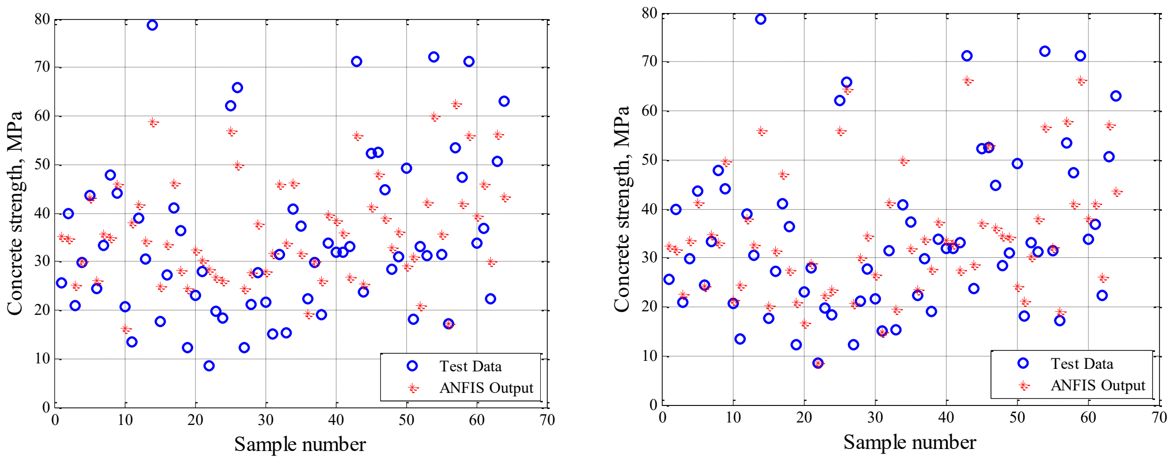
Table 5. ANFIS models for sensitivity analysis of the input numbers

| Model | Input parameter |
|---|---|
| ANFIS0 | CEM, WTR, COA, FIA |
| ANFIS1 | CEM, WTR, COA, FIA, BFS |
| ANFIS2 | CEM, WTR, COA, FIA, BFS, FLA |
| ANFIS3 | CEM, WTR, COA, FIA, BFS, FLA, SPP |

Table 6. Performance results for sensitivity analysis of the number of inputs

| Model | RMSE for testing | Number of inputs |
|---|---|---|
| ANFIS0 | 10.01 | 4 |
| ANFIS1 | 8.28 | 5 |
| ANFIS2 | 7.74 | 6 |
| ANFIS3 | 7.73 | 7 |

The performance results of the sensitivity analysis for the number of input parameters are listed in Table 6. The analysis was started at the ANFIS0 model with four inputs. The last analysis was performed for the ANFIS3 model with the entire seven input variables. The output of these models was the compressive strength of concrete at 28 days. The RMSE indication calculated for the data test set was used to evaluate the performance of each model. The final value of RMSE was evaluated without considering the reducing rate.




(a) ANFIS0 (b) ANFIS2

Figure 8. Performance of two ANFIS models for test set

As presented in Table 6, the RMSE value decreased with an increase in the number of input parameters in the model. That means, the prediction accuracy of the ANFIS model increased along with the rise in the number of input parameters. In other words, the greater the number of inputs is, the more accuracy of the ANFIS model would be. To have a visualization on the performance of the model in analyzing the number of inputs, the results from the data test set of two selected ANFIS models were presented in Fig. 8 to control sequence.

## 5. Conclusions

In this paper, the 28-day concrete compression strength was predicted from the fresh properties of concrete with the ANFIS model. Various model configurations with different features such as type of input and output membership function, number of input membership functions and epochs, type of optimal methods were thoroughly examined. In addition, different ANFIS models with varying number of input parameters were evaluated to study the effects of the number of input parameters.

The ANFIS model performed well with the RMSE values of 5.97 MPa and 7.73 MPa for the training set and test set, respectively. Among the popular input membership functions, the application of the 'gaussmf' function in the ANFIS model produced the best prediction of the 28-day concrete compression strength. Furthermore, the ANFIS model can be used as an effective tool for analyzing the relationship between one or more inputs to the output via the two-dimensional plots and the surface diagrams. Finally, based on the results from the sensitivity input analysis, it was concluded that the prediction accuracy of the ANFIS model was proportional to the increase in the number of input parameters.

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