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Neuro-fuzzy based approach for estimation of concrete compressive strength

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Abstract. Compressive strength is one of the most important engineering properties of concrete, and testing of the compressive strength of concrete specimens is often costly and time consuming. In order to provide the time for concrete form removal, re-shoring to slab, project scheduling and quality control, it is necessary to predict the concrete strength based upon the early strength data. However, concrete compressive strength is affected by many factors, such as quality of raw materials, water cement ratio, ratio of fine aggregate to coarse aggregate, age of concrete, compaction of concrete, temperature, relative humidity and curing of concrete. The concrete compressive strength is a quite nonlinear function that changes depend on the materials used in the concrete and the time. This paper presents an adaptive neuro-fuzzy inference system (ANFIS) for the prediction of concrete compressive strength. The training of fuzzy system was performed by a hybrid method of gradient descent method and least squares algorithm, and the subtractive clustering algorithm (SCA) was utilized for optimizing the number of fuzzy rules. Experimental data on concrete compressive strength in the literature were used to validate and evaluate the performance of the proposed ANFIS model. Further, predictions from three models (the back propagation neural network model, the statistics model, and the ANFIS model) were compared with the experimental data. The results show that the proposed ANFIS model is a feasible, efficient, and accurate tool for predicting the concrete compressive strength.

Keywords: concrete compressive strength; adaptive neuro-fuzzy inference system; least squares method; subtractive clustering algorithm

1. Introduction

It is well recognized that concrete mixtures can be designed to provide a wide range of mechanical and durability properties to meet the design requirements of a structure. For designers, compressive strength is one of the most important engineering properties of concrete. In most cases, compressive strength requirements for concrete are at an age of 28 days. However, testing of the compressive strength of concrete specimens is often costly and time consuming. For example, to determine the compressive strength of concrete, it is necessary to process a large amount of testing samples (at least fifteen) (Ramin *et al*. 2014, Ali 2015). In order to provide the time for concrete form removal, re-shoring to slab, project scheduling and quality control, it is necessary to predict the concrete strength based upon the early strength data (Gholamreza *et al.* 2016, Mohammed *et al.* 2016, Ahmed *et al.* 2018).

On the other hand, concrete compressive strength is affected by many factors, such as quality of raw materials, water cement ratio, ratio of fine aggregate to coarse aggregates, age of concrete, compaction of concrete, temperature, relative humidity and curing of concrete. That is, the concrete compressive strength is a quite nonlinear function that changes depend on the materials used in the concrete and the time. Although many researchers have proposed various traditional methods for predicting the concrete compressive strength, however, such traditional prediction models have been developed with a fixed equation form based on the limited number of data and parameters. With such limitations, concrete compressive strength prediction calls for new innovative methods such as artificial neural networks (ANNs), neuro-fuzzy (NF) networks, etc. The greatest advantage of ANNs over traditional modeling techniques is their ability to capture non-linear and complex interaction between variables of the system without having to assume the form of the relationship between input and output variables. Therefore, ANNs have been successfully used in predicting concrete compressive strength recently (e.g., Ni and Wang 2000, Lee 2003, Hola and Schabowica 2005, Bilgehan 2011, Khan *et al*. 2013, Faruqi *et al*. 2015, Nikoo *et al*. 2015, Chopra *et al*. 2016). However, the main disadvantages of the ANNs approach is the large complexity of the network structure, as it represents the knowledge in terms of a weight matrix together with biases which are not accessible to user. Fuzzy modeling being one of the most competent artificial intelligence subsystem, can deal with complicated and ill-defined systems in a flexible and consistent way (Bhoopal *et al.* 2012). Therefore, an adaptive neuro-fuzzy inference system (ANFIS) is developed for the prediction of concrete compressive strength in this study. The training of fuzzy system was performed by a hybrid method of gradient

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descent method and least squares algorithm, and the subtractive clustering algorithm (SCA) was utilized for optimizing the number of fuzzy rules. In addition, we also compared the prediction performances of ANFIS, back-propagation neural network model and a statistics model.

2. Materials and method

2.1 Adaptive neuro-fuzzy inference system (ANFIS)

2.1.1 Structure of ANFIS

The ANFIS is a fuzzy Sugeno model implemented in the framework of adaptive neural networks (Jang 1993). ANFIS combines both the neural network adaptive capabilities and the fuzzy logic qualitative approach and it is considered as a good universal approximation, predictor, interpolator and estimator (Djavareshkian and Esmaeili 2013). To briefly illustrate the ANFIS architecture, two fuzzy if-then rules based on Takagi-Sugeno-Kang type fuzzy model (Takagi and Sugeno 1985) are considered:

Rule 1: If x is A_1 and y is B_1, then $f_1 = p_1 x + q_1 x + r_1$

Rule 2: If x is A_2 and y is B_2, then $f_2 = p_2 x + q_2 x + r_2$

where A_1, A_2, B_1, and B_2 are defined as membership functions for inputs x and y, respectively; p_1, q_1, r_1, p_2, q_2, and r_2 are the output function parameters. In the following, the five-layer ANFIS comprising two fuzzy rules is described as follows (Jang 1993):

Layer 1: every node i in this layer is an adaptive node with a node function

$$\begin{aligned} O_{1,i} &= \mu_{A_i}(x) \quad i=1,2 \\ O_{1,i} &= \mu_{B_i}(y) \quad i=1,2 \end{aligned} \tag{1}$$

where x, y are the input of node i, $\mu_{A_i}(x)$, $\mu_{B_i}(y)$ can adopt any fuzzy membership function (MF). In this study, the bell-shaped MFs defined below are used

$$\mu_{A_i}(x) = \frac{1}{1+\left[\left(\dfrac{x-c_i}{a_i}\right)^2\right]^{b_i}} \quad i=1,2 \tag{2}$$

where a_i, b_i, c_i are the premise parameters of the membership function, governing the bell-shaped functions accordingly.

Layer 2: the outputs of this layer can be given by

$$O_{2,i} = w_i = \mu_{A_i}(x)\cdot\mu_{B_i}(y) \quad i=1,2 \tag{3}$$

where w_i indicates the firing strength of a rule.

Layer 3: every node in this layer computes the normalized firing strength as

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2} \quad i=1,2 \tag{4}$$

where $\overline{w}_i$ is referred to as the normalized firing strengths.

Layer 4: all nodes in this layer are adaptive. The output of each node is simply the product of normalized firing strength and a first-order polynomial

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i\left(p_i x + q_i y + r_i\right) \tag{5}$$

where p_i, q_i and r_i are parameters of the consequent part of rule i.

Layer 5: this layer has only one node, and the overall output of the model is given by

$$O_{5,i} = \sum \overline{w}_i f_i = \frac{\sum_i \overline{w}_i f_i}{\sum_i w_i} \tag{6}$$

It can be observed that the ANFIS has two sets of adjustable parameters, namely the premise and consequent parameters. During the training process, the premise parameters in the first layer and the consequent parameters in the fourth layer are tuned until the desired response of the FIS is achieved. When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. A hybrid algorithm combining the least squares method and the gradient descent method is employed in this study to solve this problem. The least squares method is used to optimize the consequent parameters with the premise parameters fixed, while the gradient descent method is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. When the premise parameter values of the MFs are fixed, the output of the ANFIS can be written as a linear combination of the consequent parameters

$$\begin{aligned} f &= \left(\overline{w}_1 x\right)p_1 + \left(\overline{w}_1 y\right)q_1 + \left(\overline{w}_1\right)r_1 \\ &\quad + \left(\overline{w}_2 x\right)p_2 + \left(\overline{w}_2 y\right)q_2 + \left(\overline{w}_2\right)r_2 \end{aligned} \tag{7}$$

where p_1, q_1, r_1 , p_2, q_2, and r_2 are consequent parameters.

2.1.2 Subtractive clustering algorithm (SCA)

One of the important tasks to design a fuzzy system is to determine the number of rules. There are two approaches to generate initial fuzzy rules: manually and automatically. The manual approach forces designers to spend much time on tuning fuzzy rules. In many cases the expert's knowledge is fault and may contain uncertainty, so that the manual approach is difficult to generate suitable rules. Subtractive clustering is a method that can be used to define MFs and to automatically generate rules. The subtractive clustering algorithm is based on a measure of the density of data points in which a data point with many neighboring points has the potential to be the cluster center.

Considering a collection of n data points $\{x_1,x_2,\ldots,x_n\}$ in an M dimensional space. Each data point is a candidate for cluster centers; a density measure at data point x_i is defined as

$$D_i = \sum_{j=1}^{n} \exp\left[-\frac{\left\|x_i - x_j\right\|^2}{\left(\dfrac{r_a}{2}\right)^2}\right] \tag{8}$$

where $\|\cdot\|$ denotes the Euclidean distance, and r_a is a positive constant representing a neighborhood radius. The potential of a data point to be a cluster center is when it has a high density value, which means that more data points are closer to it.

Let x_{c1} be the first cluster center and D_{c1} the potential value. The potential value for each data point is defined as

$$D_i = D_i - D_{c1} \exp\left[-\frac{\|x_i - x_{c1}\|^2}{\left(\frac{r_b}{2}\right)^2} \right] \tag{9}$$

where r_b is a positive constant that defines a neighborhood that has measurable reductions in density. The constant r_b is normally larger than r_a to prevent closely spaced cluster centers; generally r_b is equal to 1.5 r_a. After the density for each data point is recalculated, the next cluster center x_{c2} is selected and all of the densities for data points are recalculated again. This process is repeated until

$$D_{ck} < \varepsilon D_{c1} \tag{10}$$

where D_{ck} is the potential value of the k^{th} cluster center; ε is a small fraction and is an important factor that will affect the result. Chiu (1994) suggested ε=0.15.

2.2 Back propagation (BP) neural network

In artificial neural networks, BP neural network is one of the powerful tools for prediction of nonlinearities. It mainly consists of three layers: input layer, hidden layer, and output layer. The neighboring layers are fully interconnected by weights. That is, each neuron in the input layer is connected to all of the neurons in the first hidden layer. Each of the neurons in the first hidden layer is connected to each output neuron. Further, each of the neurons in the input layer is connected to each output neuron.

2.3 Statistical analysis

In this study, concrete compressive strength is considered to be the outcome of seven parameters i.e., cement (*C*), blast furnace slag (*BFS*), fly ash (*F*), water (*W*), superplasticizer (*S*), coarse aggregate (*CA*), and fine aggregate (*FA*). To generate multivariate relation based on the main data (425 datasets), the MS Excel was used and the obtained regression equation is

$$\begin{aligned} f_c = &-95.66 + 0.1688 \cdot C + 0.1441 \cdot BFS + 0.1059 \cdot F \\ &- 0.065 \cdot W + 0.1107 \cdot S + 0.0403 \cdot CA + 0.0537 \cdot FA \end{aligned} \tag{11}$$

2.4 Performance evaluation

To validate and compare the acquired results from the ANFIS, BP, and that of the statistical method (Eq. (11)), three statistical indexes are used, that is, root mean squared error (*RMSE*), mean absolute error (*MAE*) and coefficient of determination (R^2) (Roshani *et al.* 2015, Zadeh *et al.* 2016).

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{n}} \tag{12}$$

Table 1 Statistics analysis of datasets (data from Yeh 1998)

Variable	Maximum	Minimum	Average
Cement (kg/m^3)	540	102	265.44
Blast Furnace Slag (kg/m^3)	359.4	0	86.29
Fly Ash (kg/m^3)	200.1	0	62.79
Water (kg/m^3)	247	121.8	183.06
Superplasticizer (kg/m^3)	32.2	0	6.99
Coarse Aggregate (kg/m^3)	1145	801	956.06
Fine Aggregate (kg/m^3)	992.6	594	764.38
28-day CCS (MPa)	81.75	8.54	36.75

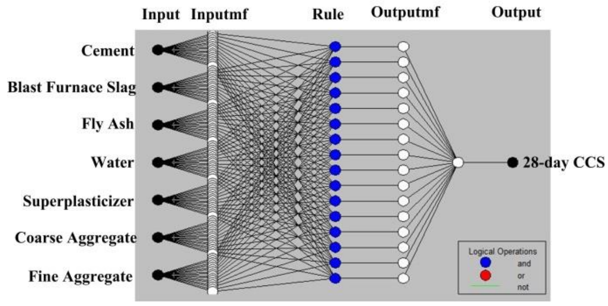


Fig. 1 ANFIS model structure

$$MAE = \frac{\sum_{i=1}^{n} |y_i - \hat{y}_i|}{n} \tag{13}$$

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i - \hat{y}_i)^2}{\sum_{i=1}^{n} (y_i - \tilde{y}_i)^2} \tag{14}$$

where y_i, $\hat{y}_i$ and $\tilde{y}_i$ are the predicted, actual and averaged actual output of the network, respectively, and n is the total number of patterns.

3. Case study

3.1 Datasets

In this study, the following seven factors, such as the cement, blast furnace slag, fly ash, water, superplasticizer, coarse aggregate, and fine aggregate were taken into account as the input parameters of the models of ANFIS, BP, and Eq. (11). The 28-day concrete compressive strength (CCS) is the output of ANFIS, BP, and Eq. (11). The database used in this study was taken from Yeh (1998) and the total number of datasets is 425. The first 340 of the total data were used to train the ANFIS model, whereas the remaining 85 of the data were used to verify the accuracy and the effectiveness of the trained ANFIS model (as shown in Table 1).

3.2 Results and discussion

The ANFIS model structure consists of 7 inputs, 16

Table 2 Different parameter types and their values used for training ANFIS

ANFIS parameter type	ANFIS (SCA)
Number of fuzzy rules	16
Number of nodes	266
Number of linear parameters	128
Number of nonlinear parameters	224
Total number of parameters	352
Number of training data pairs	340
Number of checking data pairs	85

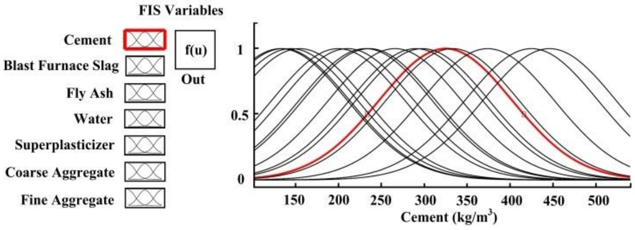


Fig. 2 Membership functions of the cement

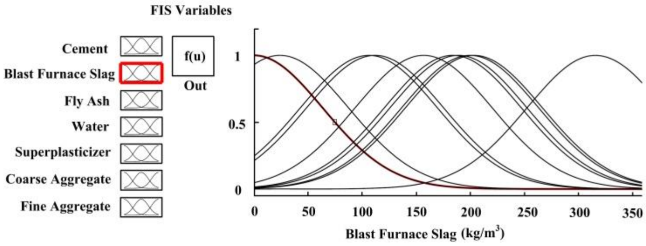


Fig. 3 Membership functions of the blast furnace slag

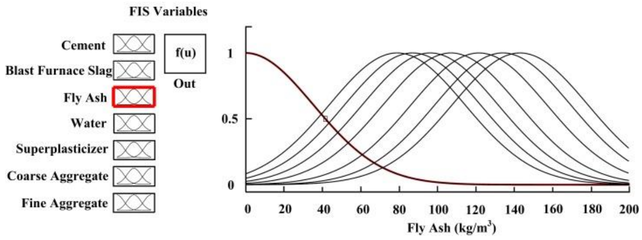


Fig. 4 Membership functions of the fly ash

input membership functions (MFs), 16 output membership functions (MFs) and 1 output, as shown in Fig. 1. Different parameter types and their values used for training ANFIS are shown in Table 2. The final Gaussian-shaped MFs of the input parameters after training are shown in Figs. 2-8, respectively.

Notice that all the inputs and outputs in Figs. 2-8 have exactly 16 MFs. The 16 MFs represent the 16 clusters that were identified by subcluster. By default, the first membership function (the red curve as shown in Figs. 2-8) would be selected in the membership function editor. For example, the parameters of the first membership function named *in1cluster1* (the red curve as shown in Fig. 2) are [77.43 325], where 77.43 represents the spread coefficient of the Gaussian curve and 325 represents the center of the Gaussian curve. *In1cluster1* captures the position and influence of the first cluster for the input variable cement. Similarly, the position and influence of other clusters for the

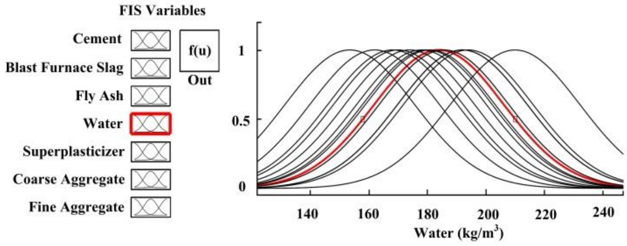


Fig. 5 Membership functions of the water

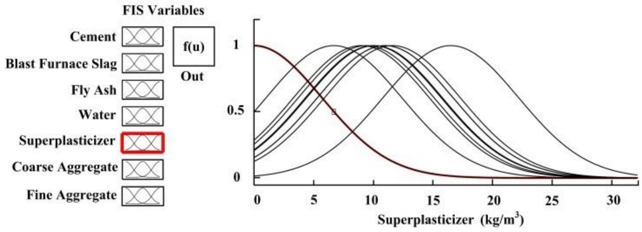


Fig. 6 Membership functions of the superplasticizer

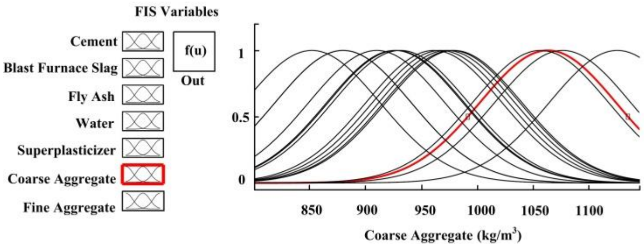


Fig. 7 Membership functions of the coarse aggregate

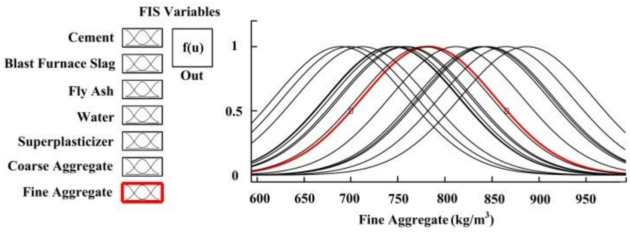


Fig. 8 Membership functions of the fine aggregate

input variables are captured by the other MFs. The parameters of the first membership functions in Figs. 3-8 are [63.53 0.0], [35.36 0.0], [22.13 184], [5.692 0.0], [60.81 1063], [70.46 783], respectively.

In addition, there are 16 rules generated based on ANFIS modeling and they are listed as follows:

1. If cement is *in1cluster1*, and blast furnace slag is *in2cluster1*, and fly ash is *in3cluster1*, and water is *in4cluster1*, and superplasticizer is *in5cluster1*, and coarse aggregate is *in6cluster1*, and fine aggregate is in*in7cluster1*, then *out1* is *out1cluster1* (1);
2. If cement is *in1cluster2*, and blast furnace slag is *in2cluster2*, and fly ash is *in3cluster2*, and water is *in4cluster2*, and superplasticizer is *in5cluster2*, and coarse aggregate is *in6cluster2*, and fine aggregate is in *in7cluster2*, then *out1* is *out1cluster2* (1);
3. If cement is *in1cluster3*, and blast furnace slag is *in2cluster3*, and fly ash is *in3cluster3*, and water is *in4cluster3*, and superplasticizer is *in5cluster3*, and coarse aggregate is *in6cluster3*, and fine aggregate is in

in7cluster3, then *out1* is *out1cluster3* (1);

4. If cement is *in1cluster4*, and blast furnace slag is *in2cluster4*, and fly ash is *in3cluster4*, and water is *in4cluster4*, and superplasticizer is *in5cluster4*, and coarse aggregate is *in6cluster4*, and fine aggregate is in *in7cluster4*, then *out1* is *out1cluster4* (1);

5. If cement is *in1cluster5*, and blast furnace slag is *in2cluster5*, and fly ash is *in3cluster5*, and water is *in4cluster5*, and superplasticizer is *in5cluster5*, and coarse aggregate is *in6cluster5*, and fine aggregate is in *in7cluster5*, then *out1* is *out1cluster5* (1);

6. If cement is *in1cluster6*, and blast furnace slag is *in2cluster6*, and fly ash is *in3cluster6*, and water is *in4cluster6*, and superplasticizer is *in5cluster6*, and coarse aggregate is *in6cluster6*, and fine aggregate is in *in7cluster6*, then *out1* is *out1cluster6* (1);

7. If cement is *in1cluster7*, and blast furnace slag is *in2cluster7*, and fly ash is *in3cluster7*, and water is *in4cluster7*, and superplasticizer is *in5cluster7*, and coarse aggregate is *in6cluster7*, and fine aggregate is in *in7cluster7*, then *out1* is *out1cluster7* (1);

8. If cement is *in1cluster8*, and blast furnace slag is *in2cluster8*, and fly ash is *in3cluster8*, and water is *in4cluster8*, and superplasticizer is *in5cluster8*, and coarse aggregate is *in6cluster8*, and fine aggregate is in *in7cluster8*, then *out1* is *out1cluster8* (1);

9. If cement is *in1cluster9*, and blast furnace slag is *in2cluster9*, and fly ash is *in3cluster9*, and water is *in4cluster9*, and superplasticizer is *in5cluster9*, and coarse aggregate is *in6cluster9*, and fine aggregate is in *in7cluster9*, then *out1* is *out1cluster9* (1);

10. If cement is *in1cluster10*, and blast furnace slag is *in2cluster10*, and fly ash is *in3cluster10*, and water is *in4cluster10*, and superplasticizer is *in5cluster10*, and coarse aggregate is *in6cluster10*, and fine aggregate is in *in7cluster10*, then *out1* is *out1cluster10* (1);

11. If cement is *in1cluster11*, and blast furnace slag is *in2cluster11*, and fly ash is *in3cluster11*, and water is *in4cluster11*, and superplasticizer is *in5cluster11*, and coarse aggregate is *in6cluster11*, and fine aggregate is in *in7cluster11*, then *out1* is *out1cluster11* (1);

12. If cement is *in1cluster12*, and blast furnace slag is *in2cluster12*, and fly ash is *in3cluster12*, and water is *in4cluster12*, and superplasticizer is *in5cluster12*, and coarse aggregate is *in6cluster12*, and fine aggregate is in *in7cluster12*, then *out1* is *out1cluster12* (1);

13. If cement is *in1cluster13*, and blast furnace slag is *in2cluster13*, and fly ash is *in3cluster13*, and water is *in4cluster13*, and superplasticizer is *in5cluster13*, and coarse aggregate is *in6cluster13*, and fine aggregate is in *in7cluster13*, then *out1* is *out1cluster13* (1);

14. If cement is *in1cluster14*, and blast furnace slag is *in2cluster14*, and fly ash is *in3cluster14*, and water is *in4cluster14*, and superplasticizer is *in5cluster14*, and coarse aggregate is *in6cluster14*, and fine aggregate is in *in7cluster14*, then *out1* is *out1cluster14* (1);

15. If cement is *in1cluster15*, and blast furnace slag is *in2cluster15*, and fly ash is *in3cluster15*, and water is *in4cluster15*, and superplasticizer is *in5cluster15*, and coarse aggregate is *in6cluster15*, and fine aggregate is in *in7cluster15*, then *out1* is *out1cluster15* (1);

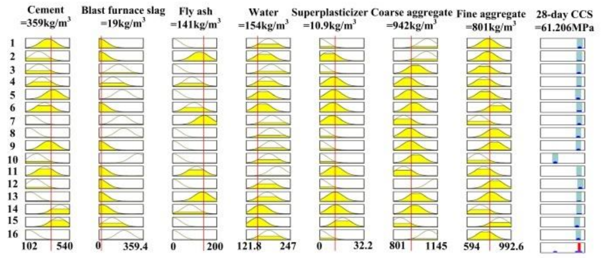
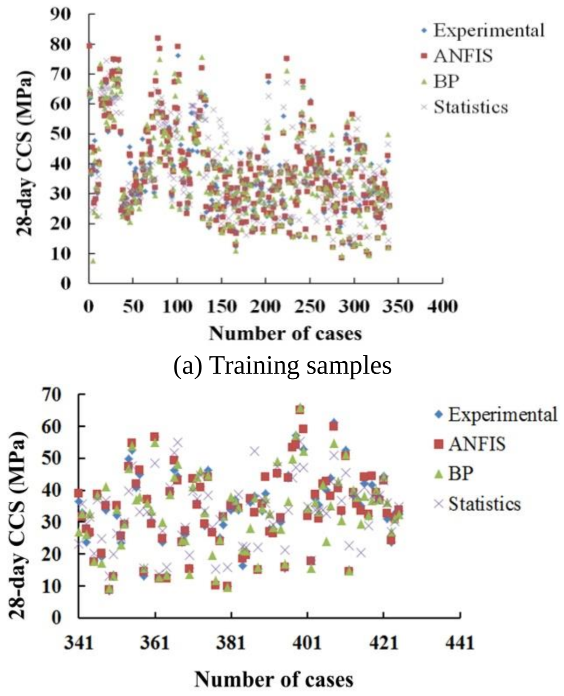


Fig. 9 Graphical illustration of fuzzy model application



(a) Training samples

(b) Testing samples

Fig. 10 Comparison between the forecasted and experimental results

16 If cement is *in1cluster16*, and blast furnace slag is *in2cluster16*, and fly ash is *in3cluster16*, and water is *in4cluster16*, and superplasticizer is *in5cluster16*, and coarse aggregate is *in6cluster16*, and fine aggregate is in *in7cluster16*, then *out1* is *out1cluster16* (1);

The developed fuzzy model can provide a precise evaluation of concrete compressive strength once we enter proper input data. Fig. 9 shows a model application in MATLAB environment. When input parameters are cement=359 kg/m^3, blast furnace slag=19 kg/m^3, fly ash=141 kg/m^3, water=154kg/m^3, superplasticizer=10.9 kg/m^3, coarse aggregate=942 kg/m^3, fine aggregate=801 kg/m^3, the 28-day CCS (Out 1) would be 61.206MPa (Fig. 9). Since the model has the ability of interpolating input parameters, that is, if we take any value between the minimum and the maximum of the dataset, the proposed ANFIS model is capable of predicting the 28-day CCS.

To evaluate the performance of the proposed ANFIS method, a comparison between the experimental results and the predictions by the BP model, the ANFIS model, and statistical method (Eq. (11)) are made and shown in Fig. 10 and Table 3, respectively. It should be noted that it is very

Table 3 Performance comparison among different models

Models	*MAE*		R^2		*RMSE*	
	Training	Testing	Training	Testing	Training	Testing
ANFIS	1.0616	1.3492	0.9939	0.9887	1.6607	1.8758
BP	3.4499	2.6992	0.9341	0.9505	5.4396	3.9084
Eq. (11)	5.4433	4.4901	0.8741	0.8989	7.3333	5.6335

important to select the number of hidden layers and the number of neurons in various layers before using the BP neural network. The number of neurons in input and output layers is usually dictated by the nature of the problem. In this study, there are 7 parameters including the cement, blast furnace slag, fly ash, water, superplasticizer, coarse aggregate, and fine aggregate were taken into account as the input parameters, therefore, the number of neurons in input layers is 7. As mentioned, the main objective of this paper is to predict the 28-day CCS, so the number of neurons in output layer is 1 and one hidden layer BP neural network is adopted herein. For the number of neurons in hidden layer, the main strategy is to use as few hidden layer neurons as possible, because each unit adds to the loads on the CPU during simulations. If the network fails to converge to a solution, it means that more hidden neurons are required. If it does converge we might try for fewer hidden neurons. Based on this idea the number of hidden neurons were determined by trial and found suitable network with 10 neurons in hidden layer. Thus, the structure of BP neural network is designed as 7-10-1. Many kinds of transfer functions have been proposed in literature and one of the most popular hidden layer transfer functions is the tangent sigmoid function, therefore, the tangent sigmoid transfer function is employed in the hidden layer herein. Because the pureline transfer function is sufficient for BP neural network to approximate almost any complex function, therefore, it is employed in the output layer in this study.

As shown in Table 3, the performance of ANFIS model is superior to those of BP and statistics method (Eq. (11)). For example, the *RMSE* of ANFIS, BP and Eq. (11) for training and testing are 1.6607 and 1.8758, 5.4396 and 3.9084, 7.3333 and 5.6335, respectively. The *MAE* of ANFIS, BP and Eq. (11) for training and testing are 1.0616 and 1.3492, 3.4499 and 2.6992, 5.4433 and 4.4901, respectively. Whereas the R^2 of ANFIS, BP and Eq. (11) for training and testing are 0.9939 and 0.9887, 0.9341 and 0.9505, 0.8741 and 0.8989, respectively. Clearly, the smaller the *RMSE* and *MAE* values and the bigger the R^2 values, the better the prediction accuracy and vice versa. However, different from the BP model and statistics method, the ANFIS model has the fuzzy logic capabilities to interpret in terms of linguistic variables, while this capability lacks in the BP model and statistics method. These results indicate that the ANFIS is a valid tool to predict the concrete compressive strength.

4. Conclusions

In this study, the adaptive neuro-fuzzy inference system (ANFIS) is developed for the prediction of 28-day concrete compressive strength. The training of fuzzy system was performed by a hybrid method of gradient descent method and least squares method and the subtractive clustering algorithm was utilized for optimizing the number of fuzzy rules. In addition, we compared the prediction performances of ANFIS, BP model, and a statistics method. The results confirmed that the developed fuzzy model, ANFIS, can provide a precise evaluation of concrete compressive strength if proper input data are provided. Moreover, the ANFIS model has the ability of interpolating input parameters and the predictions can be made in various conditions. Therefore, ANFIS may be one of the most competent artificial intelligence subsystems to evaluate the concrete compressive strength.

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