Compressive Strength Modelling of High Performance Concrete by Anfis

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Abstract

High-performance concrete (HPC) outreach the properties and constructability of normal concrete. Some of the properties required for HPC include high strength, high early strength, high modulus of elasticity, improved abrasion resistance, excellent durability and long life in severe environments, low permeability and diffusion, resistance to chemical attack, increased resistance to frost and de-icer scaling damage, toughness and impact resistance. Plasticizers are usually added to make these concretes more fluid and workable. The concrete made up of partial replacement of cement with silica fume and fly ash along with addition of steel fibre and glass fibre are adopted for this study. An adaptive neuro-fuzzy inference system (ANFIS) is a form of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. It is widely used in civil engineering area application. In this work, adaptive neuro – fuzzy inference system model was created to determine the compressive strength of concrete that contains various proportions of silica fume and fly ash as partial replacement and additional material that includes steel fibre and glass fibre.

Key words: High performance concrete, ANFIS, Grid partition method, Membership functions, Root mean square error.

1. Introduction

Any concrete which satisfies certain criteria proposed to overcome limitations of conventional concrete may be called as High Performance Concrete. It may include concrete which provides either substantially improved resistance to environmental influences or substantially increased structural capacity while maintaining adequate durability. It may also include concrete which significantly reduces construction time to permit rapid opening or reopening of roads to traffic, without compromising long-term serviceability. Therefore it is not possible to provide a unique definition of High Performance Concrete without considering the performance requirements of the intended use of the concrete. Typically, such concretes will have a low water-cementing materials ratio of 0.20 to 0.45. Plasticizers are usually used to make these concretes fluid and workable. High-performance concrete almost has a higher strength than normal concrete. However, strength is not always the primary required property.

Faezehossadat Khademi , et al(2016) studied Artificial Neural Network (ANN), Adaptive Neuro-Fuzzy Inference System (ANFIS), and Multiple Linear Regression (MLR) to predict the 28 days compressive strength of recycled aggregate concrete (RAC) and concluded that evaluation of 28 days compressive strength of recycled aggregate concrete was performed better by ANN and ANFIS in comparison to MLR. Ali nazari and Jay G sanjayan (2014) used a hybrid adaptive neuro-fuzzy interfacial systems–imperialist competitive algorithm (ANFIS-ICA) to determine the effect of concentration of alkali solution, alkali binder to alkali solution weight ratio, alkali activator to ordinary portland cement (OPC) weight ratio, oven curing temperature, and age of curing on the compressive strength of OPC-based geopolymers. Optimization of the type and number of membership functions was carried out by ICA while the training, testing and validating of the collected data sets was conducted by ANFIS

Zhe yuan, et al (2014) considered the genetic based algorithm and adaptive network-based fuzzy inference system (ANFIS) and the results of the proposed models were discussed by R^2 which is 0.813 and 0.950 in GA based ANN model and ANFIS model respectively, and RMSE which is 2.22 and 1.46 in GA based ANN model and ANFIS model respectively. Sadrmomtazi et al(2013) dealt with developing and comparing parametric regression, neural network (ANN) and adaptive network-based fuzzy inference system (ANFIS) models for predicting the compressive strength of EPS concrete. The results shows that ANN model constructed with two hidden layers and comprised of three neurons in each layers, could be effectively used for prediction purposes. Moreover, ANFIS elite model developed by bell-shaped membership function was recognized as a proper model.

Behouz Ahmadi-Nedushan, (2012) proposesd an adaptive network-based fuzzy inference system (ANFIS) model and three optimized nonlinear regression models to predict the elastic modulus of normal and high strength concrete. The results of the analyses indicate that the ANFIS outperforms the optimal nonlinear regression models for both HSC and NSC data. The RMSE values of ANFIS models for test data are 2.79 and 2.20 MPa for HSC and NSC respectively. Jafar Sobhani and Meysam Najimi, (2010) considered concrete constituents as input variables from which several regression, neural networks (NNT) and ANFIS models are constructed, trained and tested to predict the 28-days compressive strength of no-slump concrete (28-CSNSC). Comparing the results indicated that NNT and ANFIS models are more feasible in predicting the 28-CSNSC than the proposed traditional regression models.

Mohammed Sonebi and Abdulkadir Cevik (2009) used neurofuzzy (NF) approach to model the fresh and hardened properties of SCC containing pulverised fuel ash (PFA) as based on experimental data investigated in this paper. Compared to the experimental results, the proposed NF models gave accurate predictions for all of the parameters considered in this study. Tesfamariam and Najjaran (2007) used the adaptive neuro-fuzzy inferencing system to train a fuzzy model and estimate concrete strength. The efficiency of the proposed method was verified using actual concrete mix proportioning datasets reported in the literature, and the corresponding coefficient of determination r^2 range from 0.970–0.999. Further, sensitivity analysis was carried out to highlight the impact of different mix constituents on the estimate concrete strength.

An adaptive neuro-fuzzy inference system or adaptive network-based fuzzy inference system (ANFIS) is a kind of artificial neural network that is based on Takagi–Sugeno fuzzy inference system. The technique was developed in the early 1990s. Since it integrates both neural networks and fuzzy logic principles, it has potential to capture the benefits of both in a single framework. Its inference system corresponds to a set of fuzzy IF–THEN rules that have learning capability to approximate nonlinear functions. Hence, ANFIS is considered to be a universal estimator. For using the ANFIS in a more efficient and optimal way, one can use the best parameters obtained by genetic algorithm.

Current study introduced ANFIS as a tool to develop a fuzzy model that can estimate compressive strength of high performance concrete given its mix proportion. The results are verified using root mean square error value of compressive strength value of model.

2. Methodology of anfis

Adaptive Neuro Fuzzy Inference System (ANFIS) is identified as a universal estimator for responding to complex problems. ANFIS is a class of adaptive, multi-layer and feed-forward networks which is comprised of input– output variables and a fuzzy rule base of the Takagi–Sugeno type. The fuzzy reasoning mechanism of ANFIS model with two fuzzy if-then rules for a first-order Sugeno fuzzy model is expressed as (Mosavi and Nik, 2015)

Rule 1: IF x is A1 and y is B1, THEN f1 = p1x +q1y + r1.

Rule 2: IF x is A2 and y is B2, THEN f2 = p2 x +q2 y + r2.

The framework of ANFIS contains five layers, which act differently from each other; however, the nodes of the same layer perform similar to each other. The structure of ANFIS model is presented in Figure 1(Faezehossadat khademi, et al, 2016).

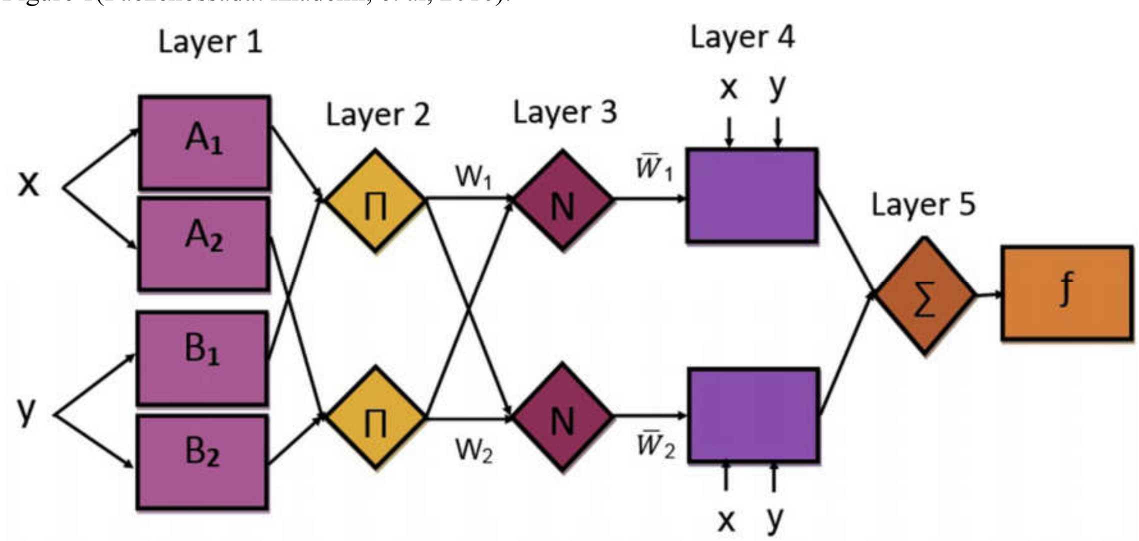

Figure 1 Structure of ANFIS model .

The structure of ANFIS is comprised of five different layers which are explained briefly in the following:

Layer 1: This layer takes the responsibility for fuzzification of input feature values in the range of 0 to 1. The required values such as membership functions for each i^{th} node are defined in this layer, shown in equation (1)

$$O_i^1 = \mu_{Ai}(x) \tag{1}$$

where x is the input to node i and A_i is the linguistic label associated with this node function.

Layer 2: Each rule is a node in the ANFIS by using softmin or product to find out the rule matching factor w_i. The incoming signals are multiplied in this layer and sent the product out, shown in equation (2)

$$O_i^2 = \mu_{Ai}(y) \times \mu_{Bi}(y),\ i = 1,2 \tag{2}$$

Layer 3: The membership values are getting normalized in this layer. The formulation of normalized firing strength for node ith in this layer is shown in equation (3)

$$O_i^3 = \frac{\mathrm{Wi}}{\mathrm{W1} + \mathrm{W2}}, \qquad i = 1,2 \tag{3}$$

Layer 4: This layer is able to establish the relationship. between the input and output values, shown in equation (4)

$$O_i^4 = w_i(p_i x + q_i y + r_i) \tag{4}$$

where w_i is the output resulted from layer 3, and $\{p_i, q_i, r_i\}$ is the parameter set.

Layer 5: This layer which is also called the defuzzification layer consists of one single node which generates the summation of all incoming signals from previous node and results in a single value. In this layer, each rule output is added to the output layer. Overall output can be calculated using equation (5)

$$O_i^5 = \sum_i \overline{w}_i f_i = \frac{\sum_i w\mathrm{ifi}}{\sum_i w\mathrm{i}} \tag{5}$$

3. Data collection

Totally 20 records of HPC were collected to construct the training and testing database. The HPC was made up of cement, silica fume, fly ash, fine aggregate, coarse aggregate, steel fibre, glass fibre, superplastiziser and water. From the ingredients of HPC, cement, fly ash, steel fibre, glass fibre by weight per unit volume taken as input variable and silica fume, fine aggregate, coarse aggregate, superplastiziser, water content are constant throughout the study, so it is not considered in the input variable. The output parameter is compressive strength at 7, 28, 56 and 90 days. The Table 1 and 2 shows the prepared mixture proportions and compressive strength after 7, 28, 56 and 90 days of curing. Moreover Table 3 summarizes the range of input and output of total data used for modelling purposes.

Table 1 Input variable value for creating model

Mix ID	SF (%)	FA (%)	STF (%)	GF (%)	C (kg/m^3)	SF (kg/m^3)	FA (kg/m^3)	STF (Kg/m^3)	GF (Kg/m^3)
M1	5	0	0.6	0	506.66	26.67	0	47.1	0
M2	5	0	0	0.6	506.66	26.67	0	0	15.3
M3	5	0	0.3	0.3	506.66	26.67	0	23.55	7.65
M4	5	0	0.4	0.2	506.66	26.67	0	31.4	5.1
M5	5	0	0.2	0.4	506.66	26.67	0	15.7	10.2
M6	5	10	0.6	0	453.33	26.67	53.33	47.1	0
M7	5	10	0	0.6	453.33	26.67	53.33	0	15.3
M8	5	10	0.3	0.3	453.33	26.67	53.33	23.55	7.65
M9	5	10	0.4	0.2	453.33	26.67	53.33	31.4	5.1
M10	5	10	0.2	0.4	453.33	26.67	53.33	15.7	10.2
M11	5	20	0.6	0	399.99	26.67	106.67	47.1	0
M12	5	20	0	0.6	399.99	26.67	106.67	0	15.3
M13	5	20	0.3	0.3	399.99	26.67	106.67	23.55	7.65
M14	5	20	0.4	0.2	399.99	26.67	106.67	31.4	5.1
M15	5	20	0.2	0.4	399.99	26.67	106.67	15.7	10.2
M16	5	30	0.6	0	346.67	26.67	159.99	47.1	0
M17	5	30	0	0.6	346.67	26.67	159.99	0	15.3
M18	5	30	0.3	0.3	346.67	26.67	159.99	23.55	7.65
M19	5	30	0.4	0.2	346.67	26.67	159.99	31.4	5.1
M20	5	30	0.2	0.4	346.67	26.67	159.99	15.7	10.2

C – Cement, FA – Fly ash, GF – Glass fibre, SF – Siicafume, STF – Steel fibre

Table 2 Output variable values for creating model

Mix ID	Average cube compressive strength (Mpa)			
	7 days	28 days	56 days	90 days
M1	45.2	61.6	66.2	71.7
M2	48.7	61.4	65.4	71.1
M3	50.3	58.8	65.3	70.6

M4	49.3	59.3	64.8	69.8
M5	48.9	58.9	64.9	69.5
M6	51.6	62.1	66.8	71.3
M7	49.6	61.7	66.2	70.2
M8	50.9	60.3	65.9	69.4
M9	50.7	60.1	65.4	69.7
M10	49.4	59.6	65.7	69.1
M11	51.2	60.5	67.8	71.8
M12	49.1	60.3	66.9	70.8
M13	50.2	59.7	66.1	70.7
M14	50.4	59.9	65.7	70.8
M15	49.2	58.6	65.9	70.4
M16	50.5	60.1	67.7	71.7
M17	48.4	59.5	65.8	70.3
M18	49.6	58.3	64.8	69.7
M19	50.1	59.5	65.2	69.8
M20	48.8	58.3	64.4	70.1

Table 3 Boundary range of input and output records

Inputs	**Range**	
	Minimum	**Maximum**
Cement (kg/m^3)	346.67	506.66
Fly ash (kg/m^3)	0	159.99
Steel fibre (kg/m^3)	0	47.1
Glass fibre (kg/m^3)	0	15.3
Output		
7 day compressive strength (MPa)	45.2	51.6
28 day compressive strength (MPa)	58.3	62.1
56 day compressive strength (MPa)	64.4	67.8
90 day compressive strength (MPa)	69.1	71.8

3.1 Training data and testing data

For 7 days compressive strength model, mix ID M1, M2, M3, M6, M7, M12, M13, M16, M17, M19 are taken as training data. For 28 days and 56 days compressive strength model, mix ID M1, M2, M6, M9, M10, M13, M15, M16, M19, M20 are taken as training data. In 90 days compressive strength model mix ID M1, M3, M7, M9, M11, M12, M15, M16, M19, M20 are taken as training data. The above mix id's were have choose the maximum and minimum values of input and output variables.

For 7 days compressive strength model, mix ID M4, M5, M8, M9, M10, M11, M14, M15, M18, M20 are taken as testing data. For 28 days and 56 days compressive strength model, mix ID M3, M4, M5, M7, M8, M11, M12, M14, M17, M18 are taken as testing data. In 90 days compressive strength model, mix ID M2, M4, M5, M5, M8, M10, M13, M14, M17, M18 are taken as testing data.

3.2 Design of anfis model

In the present study, the developed ANFIS model was used to predict the compressive strength of 7, 28, 56, 90 days of HPC containing silica fume, fly ash, steel fibre and glass fibre. The data sets are loaded using grid partition method and FIS is generated. The number of membership function for each input is taken as two and the membership type is taken as trapezoidal and Gaussian type. Membership function for the output variable is taken as constant. The hybrid optimization method was used to train membership function(MF) parameters to emulate the training data. ANFIS is trained by hybrid network for 3 numbers of epochs and process terminated by the observation of stability in error reduction.

4. Results and discussion

4.1 Modelling performance criterion

The root-mean-square error (RMSE) (or sometimes root-mean-squared error) is often used to measure the differences between values predicted by a model or an estimator and the values actually observed. The RMSE represents the sample standard deviation of the differences between predicted values and observed values. These individual differences are called prediction errors.

The performance of models is evaluated by root mean square error value as given in equation (6)

$$\text{RMSE}=\sqrt{\sum_{i=1}^{n}(\text{fc}-\text{fcp})^2/\text{n}} \quad (6)$$

f_c – Experimental compressive strength

f_{cp} – Predicted compressive strength from model

Table 4, 5, 6, and 7 shows the experimental and model predicted compressive strength of concrete for7, 28, 56, and 90 days. From that error will be calculated.

Table 4 Error prediction of compressive strength of 7 day

Mix ID	7 day compressive strength (Gaussian type MFs)		Error	Percentage error	7 day compressive strength(trapezoidal type MFs)		Error	Percentage error
	Exp	Predicted			Exp	Predicted		
M4	49.3	48.8	-0.5	1.01	49.3	47.4	-1.9	3.85
M5	48.9	50.3	1.4	2.86	48.9	49.4	0.5	1.02

M8	50.9	48.7	-2.2	4.32	50.9	47.4	-3.5	6.87
M9	50.7	49.3	-1.4	2.76	50.7	49.4	-1.3	2.56
M10	49.4	46.5	-2.9	5.87	49.4	48.8	-0.6	1.21
M11	50.2	47.6	-2.6	5.16	50.2	48.5	-1.7	3.38
M14	50.4	47.9	-2.5	4.96	50.4	51.6	1.2	2.3
M15	49.2	46.8	-2.4	4.87	49.2	48.7	-0.5	1.01
M18	49.6	49.9	0.3	0.6	49.6	51.7	2.1	4.23
M20	48.8	49.3	0.5	1.02	48.8	49.3	0.5	1.02

Table 5 Error prediction of 28 days compressive strength

Mix ID	**28 day compressive strength (Gaussian type MFs)**		**Error**	**Percentage error**	**28 day compressive strength(trapezoidal type MFs)**		**Error**	**Percentage error**
	Exp	**Predicted**			**Exp**	**Predicted**		
M3	58.8	58.5	-0.3	0.51	58.8	54	-4.8	8.163
M4	59.3	59.2	-0.1	0.16	59.3	59.3	0	0
M5	58.9	59.2	0.3	0.51	58.9	59.4	0.5	0.84
M7	61.7	59.8	-1.9	3.07	61.7	60.8	-0.9	1.45
M8	60.3	59.5	-0.8	1.32	60.3	56	-4.3	7.131
M11	60.5	61.3	0.8	1.32	60.5	60.7	0.2	0.33
M12	60.3	58.8	-1.5	2.48	60.3	59	-1.3	2.15
M14	59.9	60.2	0.3	0.50	59.9	60.4	0.5	0.83
M17	59.5	58.8	-0.7	1.17	59.5	59.5	0	0
M18	58.3	58.5	0.2	0.34	58.3	58.7	0.4	0.68

Table 6 Error prediction of 56 days compressive strength

Mix ID	**56 day compressive strength (Gaussian type MFs)**		**Error**	**Percentage error**	**56 day compressive strength(trapezoidal type MFs)**		**Error**	**Percentage error**
	Exp	**Predicted**			**Exp**	**Predicted**		
M3	65.4	63.1	-2.3	3.51	65.4	63.4	-2	3.06
M4	64.8	65.7	0.9	1.39	64.8	65.4	0.6	0.92
M5	64.9	64.3	-0.6	0.92	64.9	63.8	-1.1	1.69
M7	66.8	67.3	0.5	0.75	66.8	67.4	0.6	0.9
M8	65.9	65.2	-0.7	1.06	65.9	63.1	-2.8	4.24

M11	65.7	65.4	-0.3	0.45	65.7	65.2	-0.5	0.76
M12	66.1	65	-1.1	1.66	66.1	62.7	-3.4	5.14
M14	65.7	65.7	0	0	65.7	65.7	0	0
M17	67.7	66.8	-0.9	1.32	67.7	66.4	-1.3	1.92
M18	65.8	64.8	-1	1.52	65.8	64.4	-1.4	2.12

Table 7 Error prediction of 90 days compressive strength

Mix ID	90 day compressive strength (Gaussian type MFs)		Error	Percentage error	90 day compressive strength(trapezoidal type MFs)		Error	Percentage error
	Exp	**Predicted**			**Exp**	**Predicted**		
M2	71.1	69.5	-1.6	2.25	71.1	68.8	-2.3	3.23
M4	69.8	70.9	1.1	1.57	69.8	71.2	1.4	2
M5	69.5	69.9	0.4	0.57	69.5	68.9	-0.6	0.86
M6	71.3	71.4	0.1	0.14	71.3	71.2	-0.1	0.14
M8	69.4	69.7	0.3	0.43	69.4	67.4	-2	2.88
M10	69.1	69.7	0.6	0.86	69.1	69.1	-0	0
M13	70.7	69.5	-1.2	1.71	70.7	66.8	-3.9	5.51
M14	70.8	70.1	-0.7	1	70.8	70.3	-0.5	0.7
M17	70.3	71.1	0.8	1.13	70.3	69.8	-0.5	0.71
M18	69.8	70.5	0.7	1	69.8	71.7	1.9	2.72

The negative value in the error shows that the predicted value is less than the experimental value and the positive value shows that the predicted value is higher than the experimental value. The error in the prediction model is always less than 10 percentage. So that result obtained from prediction models are good.

4.2 Performance of anfis model

The performance of ANFIS models (ANMs) is examined by root mean square error and the results are summarised in Table 8. As seen in Table 8, all the adaptive network based inference system models have acceptable prediction performance. From these models, Adaptive network model which is constructed with trapezoidal type MFs gives best result for 7 day compressive strength and also Gaussian-type MFs exhibits the best performance for 28 days, 56days, and 90days compressive strength.

Table 8 Summary of ANMs for prediction of compressive strength of HPC

ANFIS model	Membership function type	RMSE value
ANM for 7 days	Trapezoidal	1.655
	Gaussian	1.911
ANM for 28 days	Trapezoidal	2.115
	Gaussian	0.891
ANM for 56 days	Trapezoidal	1.709
	Gaussian	1.015
ANM for 90 days	Trapezoidal	1.7589
	Gaussian	0.863

5. Conclusions

In this project, various ANFIS models were developed to predict the compressive strength of high performance concrete for 7, 28, 56, 90 days. Totally 20 high performance concrete mixtures data were used. From these data 10 data were randomly selected as training sets and the remaining 10 data were used for testing of models.

The following results were drawn from this investigation:

- ANFIS models could predict 7, 28, 56 and 90 days compressive strength with satisfactory performance owing to their distributed and parallel computing nature.
- All of the proposed ANFIS models exhibit acceptable performance. From these models, trapezoidal membership function model gives good result for prediction of 7 day compressive strength. Gaussian type membership function model presents the best performance for the prediction of 28, 56, 90 days compressive strength.
- The percentage of error for the given models should be within the limit.
- Number of membership function and type of membership function are affecting the result of model.

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