Adaptive Neuro-Fuzzy Inference System for Predicting Strength of High Performance Concrete

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Abstract

This study examines the performance of Adaptive Neuro-Fuzzy Inference System (ANFIS) for estimation of compressive strength of High Performance Concrete (HPC) from given mix proportion. An ANFIS model merges advantages of both ANN and Fuzzy Logic. A total of 54 experimental data sets were used, where 36 datasets were used in training and 18 datasets were used for validating the model. Six input parameters include water binder ratio, age of testing, silica fumes, coarse and fine aggregate and superplasticizer whereas compressive strength is the single output parameter. The experimental and obtained results were compared. The result illustrates that ANFIS model can be used as an alternate method to predict the compressive strength of High Performance Concrete.

Keywords: *High Performance Concrete, ANFIS model, training & testing, compressive strength.*

Introduction

Concrete is a composite material. It is most extensively used in the construction industry as construction material due to its good durability and strength criteria. Due to the rapid growth of construction industry in recent years, the massive volume of concrete is produced. Almost 10 billion tonnes (12 billion tons) of concrete is used in construction industry every year. Therefore, human safety is one of the important criteria which must be satisfied while producing a large volume of concrete. To fulfill this condition, maintenance of strength and durability criteria of the concrete is the major principle which must be satisfied. So effort has made to develop High Performance Concrete (HPC) which mainly emphasis on strength and durability criteria. HPC focus mainly on the strength and durability criteria. Certain characteristics of conventional concrete were developed to achieve HPC. Characteristics of HPC involve high strength and high durability (water absorption, permeability, acid attack etc.) as well as service life [1, 2]. HPC can be used to build more serviceable structure at comparatively lower cost.

Different soft computing techniques are very useful in solving complex problems. But the accuracy level can be increased if we combine two or more different soft computing technique. In this study, the neural network is combined with fuzzy logic to form ANFIS model, which is a hybrid intelligent model and provides better accuracy. In this hybrid model, neural network learning and recognizing pattern combine with fuzzy logic's human like reasoning technique [3].

Literature Review

Yeh [1] gave a technique of optimizing the mix proportions of HPC for a specified workability and compressive strength, with the help of the artificial neural network. To determine the compressive strength, models were developed. Other parameters such as initial slump, slump after 45 minutes, initial slump flow and slump flow after 45 minutes were also predicted. Tesfamariam et al. [4] suggested the use of ANFIS for estimation of concrete strength. The performance of ANFIS is checked with experimental concrete mix proportion datasets obtained from the works, and according to which range of value of r_2 range is determined which lies from 0.970–0.999. Parichatprecha et al. [5] aimed at determining the effect of the amount of water–binder ratio, water, cement as well as use of mineral admixture (silica fume and fly ash) as a fractional replacement of cement on the durability criteria of HPC with the help of ANN. The model which is prepared has the capability to predict data within its range, but this range can be easily increased by retraining the proposed model with furthermore input data. Ozcan et al. [6] predicted compressive strength of concrete with silica fume by using Artificial Neural Network (ANN) and fuzzy logic. 3, 7, 28, 180 and 500 days compressive strength were foreseen using Fuzzy Logic and ANN model. The results concluded that models of ANN and fuzzy logic may be used to calculate the compressive strength for this type of concrete.

Sobhani et al. [7] developed artificial neural network and ANFIS model which are used for forecasting of the compressive strength of concrete at 28 days with no-slump. The result shows, proposed models of ANN and ANFIS are more feasible for forecasting the compressive strength. Muthupriya et al. [8] developed two types of HPC with fly ash containing silica fume and metakaolin. Input variable includes is a specimen, cement silica fume, fly ash, water, sand, coarse aggregate and superplasticizer whereas output variable contains compressive strength. Two neural network model well prepared namely ANN-I and ANN-II. ANN-I contents one hidden layer and ANN-II contents to hidden layer. A comparative study was done between these two models. Chou et al. [9] proposed an ensemble model to predict HPC's compressive strength. The performance of Support Vector Machine (SVM), ANN, classification and regression trees etc. were applied for the development of this ensemble models. Analyzed results illustrate that best expectation performance was obtained by establishing a combination of two or more models using the ensemble technique.

Gayathri U. et al. [10] developed model using ANN for the prediction of Flexural strength, split tensile strength and compressive strength of HPC. Multilayer feed forward ANN model is used with 50000 epochs. The result shows that ANN have a high possibility for prediction of split tensile test, compressive strength at 28 days and flexural strength of HPC. Khademi et al. [11] developed three different models on ANFIS, ANN and multiple linear regression (MLR) for the calculation of compressive strength at 28 days for Recycled Aggregate Concrete. 14 different input parameters were taken. These parameters were used for the study of compressive strength at 28 days. The current study suggested that ANN and ANFIS model are more precise for calculation of compressive strength than multiple linear regressions.

From the extensive literature review it is identified that limited amount of research has been produced in the direction of High Performance Concrete using analytical modeling. So this research work focuses on using ANFIS model to reduce the cost of construction, conserve energy, and minimizing the wastage of material for achieving the required strength, by making number of trial mixes of concrete. The results reveal that experimental data can be estimated to a notably close extent Via ANFIS model.

Research Significance

The use of ANFIS model in predicting the material properties of High Performance Concrete is a new approach. The neural network approach is somewhat accurate for a wide range of data. But it is not always possible to generate a huge amount of data in the laboratory due to various problems such as cost inefficiency, shortage of availability of raw materials, time consuming, the requirement of a large number of labour etc. ANFIS model provides better accuracy where there is a shortage of data. ANFIS model involves self-adaptability for good accuracy due to the involvement of both the properties of neural network and fuzzy logic to the model. The primary objective of this work is to propose an ANFIS model with experimental data and to find the optimum amount of mineral admixture required. Also, the proposed model can be used for accurately predicting the data in future.

Methodology and Materials

Materials

In this work, cement which is used is 43Garde OPC conforming to IS 8112-1989[12] and the utilization of silica fumes has reduced the consumption of cement. Silica fume having a bulk density 750-850 kg/m3 and surface area 20000 m2/kg. Fine aggregate of Zone-II was used in the experiment [13, 14] and Specific gravity, water absorption were obtained as 2.52 and 1.15% respectively. Coarse aggregate used has a nominal size of 20mm [14] and its Specific gravity along with water absorption was obtained as 2.61 and 0.46%. In this thesis naphthalene based water reducing admixture (superplasticizer) as per IS 9103:1999 and ASTM C 494 was used [15].

Laboratory Test

The mix design was prepared using ACI 211.4R [16, 17]. High Performance Concrete was developed for 50 MPa, 55 MPa and 60 MPa strength and Silica fumes were added with cement with 0%, 2.5%, 5%, 7.5%, 10% and 12.5% of initial cement content. For each trial mix, three cubes were cast. Compressive strength test is one of the fundamental tests of concrete. It provides an idea about overall characteristics of concrete. Different factors govern the compressive strength of concrete. They are quality of raw materials, water-binder ratio, controlled environmental conditions, use of mineral and chemical admixtures etc. [18]. Compressive strength was tested in the laboratory for 28 days, 56 days and 90 days. A total of 54 experimental data sets were used, where 36 datasets were used in training and 18 datasets were used for validating the model. 24-hours water absorption test was conducted for checking the durability criteria of concrete.

ANFIS Architecture

ANFIS has been primarily used for this project. Here fusion of fuzzy logic and ANN takes place. Artificial Neural Network (ANN) is a computing tool based on the process of genetic neural networks. The ANN techniques are applicable to the problems of civil engineering, because of their potentiality of learning straightly from examples. Correct response to deficient work, their ability to extract the results from minimal data and their generalized results production are the other important properties of ANN [19]. The capabilities mentioned above give rise to ANN a very commanding mechanism to determine solution for several engineering problems, where data is insufficient [20]. The basic idea of ANN based mathematical model for material performance is, to educate an ANN system using that material for series of experiments including the enough information in the results, about the materials behaviour, to succeed as a material model [21]. Such trained ANN system replicate the outcome of experiments and also able to estimate the outcome in other experiments through their simplification potential [22]. Fuzzy logic is an approach for the computing based on the degrees of truth, instead using true or false logic. It is important to generate efficient fuzzy if-then rule in modelling because they directly affect the performance of the system [23]. This system includes a set of fuzzy linguistic rules which may be given by experts. These can also be taken out from mathematical data [24]. ANFIS mainly deals with Takagi-Sugeno fuzzy logic and this method comprises of the hybrid system. ANFIS model is chosen as the backbone for validating experimental work. The detail description of ANFIS model is provided below (Fig.1).

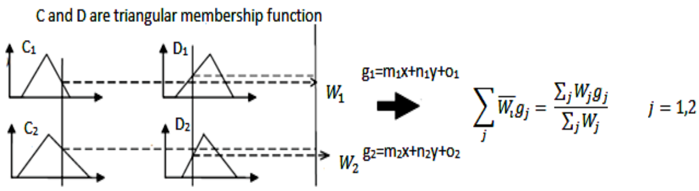


Fig.1: Functioning of ANFIS Model

Fig.2 & Fig.3 illustrates the architecture and structure of an ANFIS model having two input parameters and the mechanism of fuzzy-reasoning, respectively. For straightforwardness, let us adopt that the fuzzy inference system (FIS) has double input parameters u and v and single output parameter z. In the 1st order fuzzy model of Takagi-Sugeno, a simple instruction set with dual IF-THEN rules is provided below:

Rule I: If u is C_1 and v is D_1, then g_1=m1x+n1y+o_1 ----------------- Eq.(1)

Rule II: If u is C_2 and v is D_2, then $g_2=m_2x+n_2y+o_2$ ----------------- Eq.(2)

Here u and v are inputs, C_1, D_1, C_2 and D_2 are fuzzy set and g_1 and g_2 are crisp function. Here g_1 and g_2 are the polynomial functions for the input variables of u and v. here m_1, m_2, n_1, n_2, o_1 and o_2 are design parameters which are determined at the time of training process. When g (u,v) is a constant function, the Sugeno fuzzy model which is developed is of order zero. This can be treated as a distinctive case of Mamdani FIS. The above two rules state the 1[st] order Sugeno FIS. In the figure below square nodes are represented as an adaptive node and circular nodes are represented as a fixed node. The corresponding ANFIS structure shown as:

Layer 1: Each node 'j' of the layer is a square adaptive. The output of this layer is the fuzzy value of the original crisp value provided as input.

$$O_{(1,j)} = \mu C_j(u), \ j = 1,2 \qquad \text{----------------- Eq.(3)}$$

$$O_{(1,j)} = \mu D_{j-2}(v), \ j = 3,4 \qquad \text{----------------- Eq.(4)}$$

Here, u and v are input to node j and C_i and D_{i-2} are linguistic (fuzzy sets: small, medium, large etc.). For Gaussian membership function,

$$\mu C_j = \exp\left[-\left(\frac{x-e_j}{d_j}\right)^2\right]$$

Where, d_j and e_j are the parameters of membership function.

Layer 2: Each node of the layer is fixed circular, levelled as π. Here AND operator is used for the fuzzification of input. Output in this layer is presented by

$$O_{(2,j)} = W_i = \mu C_i(x) * \mu D_i(y), \ \ i = 1,2 \qquad \text{----------------- Eq.(5)}$$

These are known as rule's firing weight.

Layer 3: All the nodes in the layer is a fixed circular, which is represented with N. In this layer ratio of firing weight to all the firing weight is done.

$$O_{(3,j)} = \overline{W_i} = \frac{W_j}{W_1+W_2}, \quad j = 1,2 \qquad \text{----------------- Eq.(6)}$$

The output of this layer is identified as normalized firing weight.
Layer 4: The nodes of this layer square adaptive node. The output is the multipli-

cation of first-order Sugeno model (polynomial function of the first order) and the normalized firing weight.

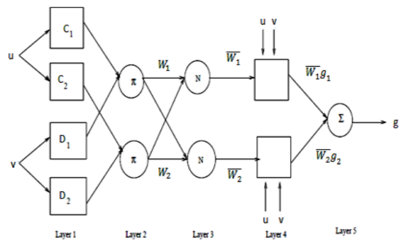
$$O_{(4,j)} = \overline{w_i} f_j = \overline{W_i}(m_1 u + n_1 v + o_1),\ j = 1,2. \qquad \text{----------------- Eq.(7)}$$

Where, $\overline{w_i}$ is the layer 3 output and p_1, q_1, r_1 are design parameters.

Layer 5: It is a single circular fixed node which is denoted by $\sum$. This node provides the output of ANFIS model.

$$O_{(5,j)} = \sum_j \overline{W_i} g_j = \frac{\sum_j W_j g_j}{\sum_j W_j} \qquad \text{----------------- Eq.(8)}$$

In this Fuzzy Logic the key learning rule is the back propagation gradient descent and in which error signals calculated recursively to the input layer from the output layer. It is same as the general feed forward neural network system. The recent development in the ANFIS is the hybrid learning method, which uses both gradient descent and least square methods to find practicable set of antecedent and consequent parameters and this latest method has been implemented in this study for the ANFIS model developed. Fuzzy Logic Toolbox with MATLAB version 7.1 was used in this method. The relationship of compressive strength as an output and six inputs that are water powder ratio, fine aggregate, coarse aggregate, glass fibre, superplasticiser in ANFIS is shown in Fig.4.



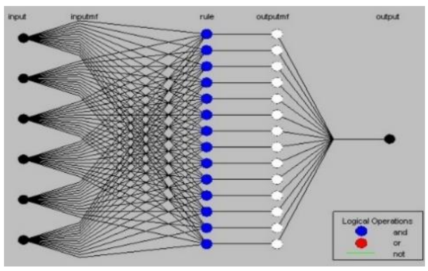
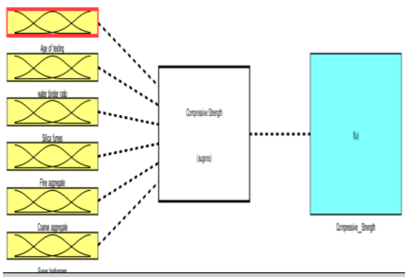


Fig. 2: Structure of ANFIS **Fig. 3**: Architecture of ANFIS model



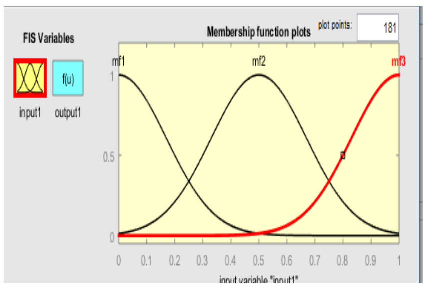


Fig. 4: Input Output data **Fig. 5:** Membership function before training

Similarly Fig.5 shows input membership function before training, Fig.6 to Fig.11 shows membership function after learning for all six input parameters respectively and Fig. 12 shows the rule viewer showing first 30 rules of total 729 rules.

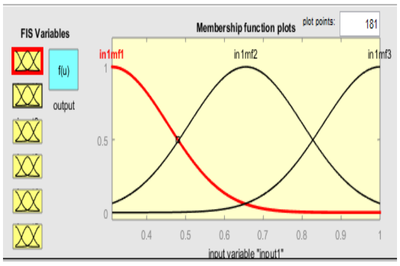


Fig. 6: Membership function for age of testing

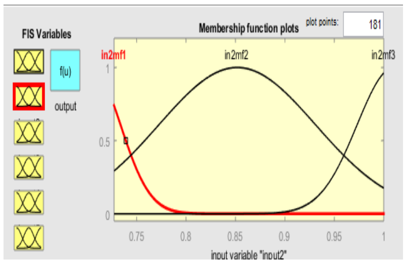


Fig. 7: Membership function for water binder ratio

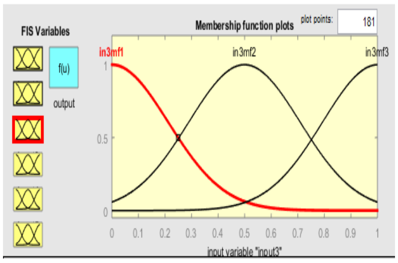


Fig. 8: Membership function for silica fumes

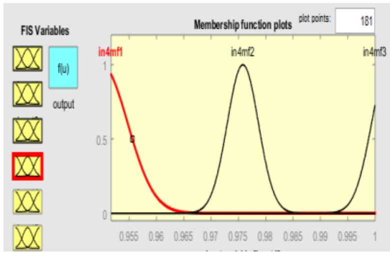


Fig. 9: Membership function for fine aggregat**e**

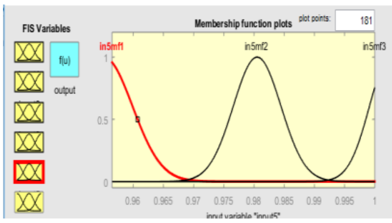


Fig. 10: Membership function for coarse aggregate

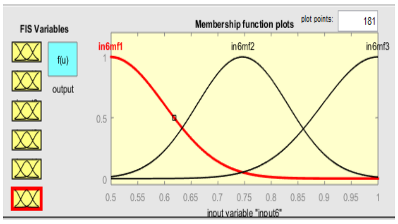


Fig.11: Membership function for superplasticizers

These rules were made during training of ANFIS model. The calculation of the output (compressive strength) is done with the help of these rules. These rules can be made either by training with available input data or manually developing the rules. These rules can be edited, changed removed and added according to the requirement of the model with the help of rule editor.

Training and Validation of ANFIS model

Training and testing data in ANFIS model set is used for the establishment of the relation between input and output. In this project, ANFIS model is developed to predict one output from a combination of six input. For this model 36 experimental data is used for training ANFIS model, whereas 18 experimental data were used in testing. The experiment was conducted with 50 MPa, 55 MPa and 60 MPa strength of concrete. Silica fumes were added with cement with 0%, 2.5%, 5%, 7.5%, 10% and 12.5% of initial cement content. Compressive strength was tested in the laboratory for 28 days, 56 days and 90 days. ANFIS model was prepared with six input parameters and one output parameters. Six input parameters as shown in Table 1are includes (a) Age of testing; (b) Water-binder ratio; (c) Silica fumes; (d) Coarse aggregate; (e) Fine aggregate and (e) Superplasticizer. Compressive Strength is the output parameter.

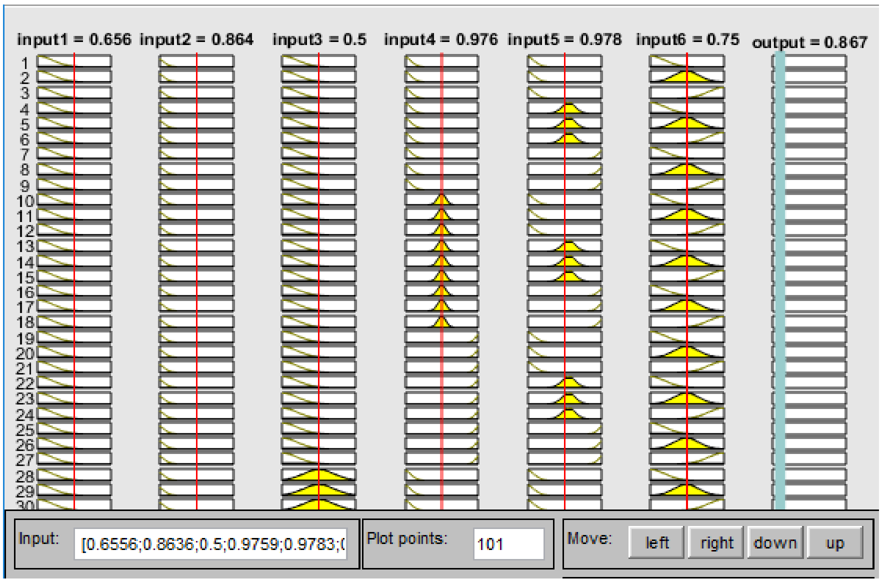


Fig. 12: Rule Viewer

Table 1 Boundary range of experimental data

Component content	Minimum	Maximum	Range	Mean	Standard Deviation
Water binder ratio	0.265	0.364	0.099	0.312	0.028
Silica fumes (kg per cum)	0	71.25	71.25	32.81	22.79
Aggregates Finer (kg per cum)	690	725	35	708.33	14.47
Aggregates Coarser(kg per cum)	1100	1150	50	1126.7	20.74
SP (l liter per cum)	4	8	4	5.922	1.296
Testing interval in days	28	90	62	58	25.589
Compressive Strength (MPa)	56.12	82.3	26.18	68.84	7.18

Training of ANFIS model was done with 0, 2.5, 7.5 and 12.5% content of silica fumes for 50 MPa concrete for 28, 56 and 90 days; 2.5, 5 10 and 12.5% content of silica fumes for 55 MPa concrete for 28, 56 and 90 days; 0, 5, 7.5 and 10% content of silica fumes for 60 MPa concrete for 28, 56 and 90 days; whereas experimentation was done with 5% and 10% content of silica fumes for 50 MPa concrete for 28, 56 and 90 days; 0% and 7.5% content of silica fumes for 55 MPa concrete for 28 days, 56 days and 90 days; 2.5% and 12.5% content of silica fumes for 60 MPa concrete for 28 days, 56 days and 90 days. During experimentation, 10% was obtained as the optimum quantity of silica fume.

Table 2 Values of parameter used in ANFIS model

Input layer neurons	6(number)
Output layer neurons	1(number)
Hidden layer	4(number)
Membership Functions (MFs) for each input	3(number)
Input MF type	Gaussmf
Output MF type	Linear
Optimum method	Hybrid
Error tolerance	0.5
Epochs	2500
Number of Rules	729

Table 3 Normalized data used for testing of ANFIS model

Sl. No	Age of testing	Water binder ratio	Silica fumes (kg/m^3)	Fine aggregates (kg/m^3)	Coarse aggregates (kg/m^3)	SP (l/m^3)
1	0.311111	0.952381	0.336842	0.951724	1	0.55
2	0.311111	0.903837	0	0.97931	0.982609	0.65
3	0.311111	0.909091	0.673684	0.951724	1	0.6
4	0.311111	0.840786	0.552561	0.97931	0.982609	0.725
5	0.622222	0.952381	0.336842	0.951724	1	0.55
6	1	0.952381	0.336842	0.951724	1	0.55
7	0.622222	0.903837	0	0.97931	0.982609	0.65
8	0.622222	0.909091	0.673684	0.951724	1	0.6
9	0.311111	0.798093	0.2	1	0.956522	0.9
10	1	0.909091	0.673684	0.951724	1	0.6
11	1	0.903837	0	0.97931	0.982609	0.65
12	0.311111	0.727151	1	1	0.956522	1
13	0.622222	0.840786	0.552561	0.97931	0.982609	0.725
14	1	0.840786	0.552561	0.97931	0.982609	0.725
15	0.622222	0.798093	0.2	1	0.956522	0.9
16	0.622222	0.727151	1	1	0.956522	1
17	1	0.798093	0.2	1	0.956522	0.9
18	1	0.727151	1	1	0.956522	1

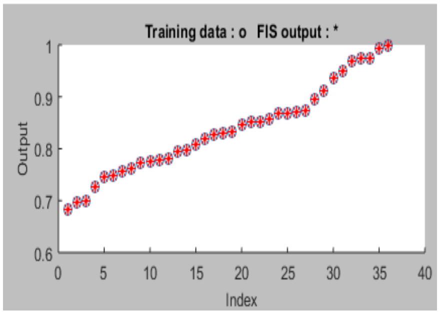


Fig. 13: Predicted result for training data

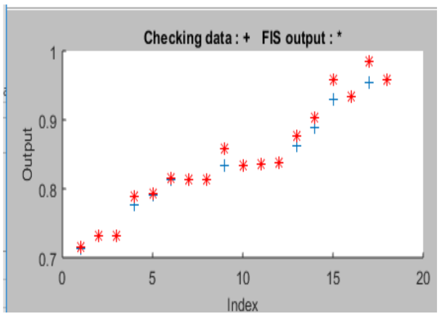


Fig. 14: Predicted result for testing data

The data provided for training the ANFIS model is arranged in ascending order with respect to the output parameter. Normalized format is applied to present the data used for training and testing. The values of parameter used in ANFIS model are shown in Table 2 and the normalized data used for testing has show in Table 3. The predictted result for training data and testing data are shown in Fig.13 & Fig.14.

Result and Discussion

ANFIS model was trained with 36 experimental data and 18 experimental data were used for validation. 2500 epochs was used during the training process as shown in Fig.15 & Fig.16. The regression (R2) value of training data was 99.99% and testing data was 98.87%. Below graph shows a correlation of both training and testing data. It is clear from the above table that data predicted by ANFIS model is very close to the experimental result. Statistical values provided in the table below shows the efficiency of ANFIS model. As the training input increases, the model will be able to perform more accurate prediction of the output parameter. During the selection of data properties of each node must not differ.

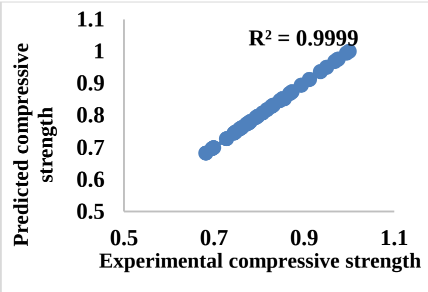


Fig.15: experimental &predicted strength during training phase

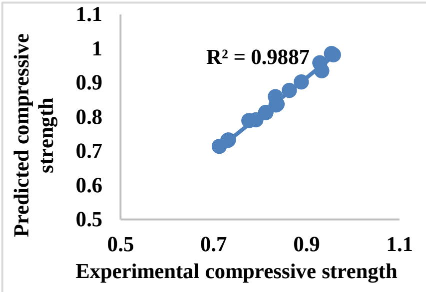


Fig.16: experimental & predicted strength during testing phase

The Table 4 shows R^2 (Regression), MAD (Mean Average Deviation), MSE (Mean Square Error), RMSE (Root Mean Square Error) and MAPE (Mean Average Percentage Error). The results in the Table 4 show that these values are within the range. The overall performance of the proposed ANFIS model is accurate. This ANFIS model can be implemented for the prediction of HPC's compressive strength. The input values must be chosen within the range input provided during training. This range can be increased by training with additional new input data.

Table 4 Performance of ANFIS model

ANFIS Database	R^2	MAD	MSE	RMSE	MAPE
Training	0.9956	0.020581	0.004621	0.067974	0.030226
Testing	0.9887	0.711677	1.391394	1.179574	0.967742

Conclusion

From the investigations, a model was developed to predict compressive strength (28 days, 56 days and 90 days) of HPC by using ANFIS and the experimental dataset is used for training and testing the ANFIS model. Training is done with 36 dataset and testing is done with 18 dataset. Input MF was taken as gaussmf and output membership function was taken as linear. A simple Feed forward back-propagation technique was used to model problems involving non-linear variables.

The developed model R, MAD, MSE, RMSE and MAPE values are calculated for training and testing, found that all are within the permissible limits. The regression (R^2) value of training data was 99.56% and testing data was 98.87%. Statistical parameters for proposed ANFIS model includes 0.020581 (MAD), 0.004621 (MSE), 0.067974 (RMSE), 0.030226 (MAPE) for training phase and 0.711677 (MAD), 1.391394 (MSE), 1.179574 (RMSE), 0.967742 (MAPE) for testing phase.

The concrete industry can take advantage from the proposed models to obtain a reliable estimate of the elastic modulus from high performance concrete. ANFIS model can predict compressive strength of concrete with satisfactory performance. This process reduces time, labour and wastage of material. The above proposed model can be extended and improved by adding a number of input parameters as well as increasing their range of data if sufficient amount of data is available.

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References

1. Yeh, I. C. Design of High Performance Concrete Mixture Using Neural Networks and Nonlinear Programming, *Cement and Concrete Research*, 28(12): 1797–1808,1998.
2. Piotr Smarzewski and Danuta Barnat-Hunek. Property Assessment of Hybrid Fiber-Reinforced Ultra-High- Performance Concrete, *International Journal of Civil Engineering*, Published online on 16th February 2017, DOI 10.1007/s40999-017-0145-3.
3. A. Sadrmomtazi, J. Sobha ni and M.A. Mirgozar. Modeling compressive strength of EPS lightweight concrete using regression, neural network and ANFIS, *Construction and Building Materials*, 42: 205‑216, 2013.
4. Tesfamariam, S., and Najjaran, H. Adaptive Network–Fuzzy Inferencing to Estimate Concrete Strength Using Mix Design, *Journal of Materials in Civil Engineering*, 19(7): 550–560, 2007.
5. Parichatprecha, R., and Nimityongskul, P. Analysis of durability of high performance concrete using artificial neural networks. *Construction and Building Materials*, Elsevier Ltd, 23(2): 910–917, 2009.
6. Özcan, F., Atiş, C. D., Karahan, O., Uncuoğlu, E., and Tanyildizi, H. Comparison of artificial neural network and fuzzy logic models for prediction of long-term compres-

sive strength of silica fume concrete, *Advances in Engineering Software*, 40(9) :856–863, 2009.

7. Sobhani, J., Najimi, M., Pourkhorshidi, A. R., and Parhizkar, T. Prediction of the compressive strength of no-slump concrete: A comparative study of regression, neural network and ANFIS models, *Construction and Building Materials*, Elsevier Ltd, 24(5): 709–718, 2010.
8. Muthupriya, P., Subramanian, K., and Vishnuram, B. G. Prediction of Compressive Strength and Durability of High Performance Concrete By Artificial Neural Networks, *International Journal of Optimization in Civil Engineering*, 1: 189–209, 2011.
9. Chou, J. S., and Pham, A. D. Enhanced artificial intelligence for ensemble approach to predicting high performance concrete compressive strength.” *Construction and Building Materials*, Elsevier Ltd, 49 :554–563, 2013.
10. Gayathri.U, Shanmugapriya.T, and Suveka.V. Predicting the strength of high performance concrete using artificial neural network, *International Journal of Applied Engineering Research ,* 11(3): 3–8, 2016.
11. T, Chandra Sekhara REDDY. Predicting the strength properties of slurry infiltrated fibrous concrete using artificial neural network, *Frontiers of Structural and Civil Engineering*.
12. Indian Standard Code IS: 8112-2013. Specifications for 43 grade ordinary Portland cement, Bureau of Indian Standards, New Delhi, India,2013.
13. Indian Standard Code IS: 2386-1997 Methods of test for aggregates for concrete, reprinted, Bureau of Indian Standards, New Delhi, India, 2002.
14. Indian Standard Code IS: 383-1970. Specification for coarse and fine aggregates from natural sources for concrete, Bureau of Indian Standards, New Delhi, India, 2002.
15. Prasad, M. L. V., Prasenjit Saha and A.I.Laskar. Behaviour of Self Compacting Reinforced Concrete Beams Strengthened with Hybrid Fiber under Static and Cyclic Loading, *International Journal of Civil Engineering*, 16(2) ; 168-179, 2018.
16. ACI Committee report ACI 211.4R-93, Guide for Selecting Proportions for High-Strength Concrete with Portland Cement and Fly Ash, *Annual Book of ASTM Standards.*
17. A. Islam Laskar and S. Talukdar . A New Mix Deign Method for High Performance Concrete , Asian Journal of Civil Engineering (building and housing) , 9 (1): 15-23, 2008 .
18. T, Chandra Sekhara REDDY. Predicting the strength properties of slurry infiltrated fibrous concrete using artificial neural network, Front. Struct. Civ. Eng, 2017,. https://doi.org/10.1007/s11709-017-0445-3.
19. Mustafa Saridemir: Prediction of compressive strength of concretes containing metakaolin and silica fume by artificial neural networks. *Advances in Engineering Software* 40: 350–355, 2009.
20. Srdan Kostic and Dejan Vasovic: Prediction model for compressive strength of basic concrete mixture using artificial neural networks. *Neural Computer & Applications* 26: 1005–1024, 2015.
21. Cahit Bilim, Cengiz D. Atis, Harun Tanyildizi and Okan Karahan: Predicting the compressive strength of ground granulated blast furnace slag concrete using artificial neural network. *Advances in Engineering Software* 40:334-340, 2009.
22. Alireza Najigivi, Alireza Khaloo, Azam Iraji zad and Suraya Abdul Rashid: An Artificial Neural Networks Model for Predicting Permeability Properties of Nano Silica–Rice Husk Ash Ternary Blended Concrete. *International Journal of Concrete Structures and Materials* 7(3):225–238, 2013.
23. Allali S. A., Abed M., Mebarki A.: Post earthquake assessment of buildings damage using fuzzy logic. *Engineering Structures* 166:117-127, 2018.
24. Dambrosio L.: Data based fuzzy logic control technique applied to a wind system. *Energy procedia* 126 (201709):690-697, 2017.