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MODELING OF COMPRESSIVE STRENGTH OF HIGH PERFORMANCE CONCRETE USING ARTIFICIAL NEURAL NETWORK

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ABSTRACT

An Artificial brain-like network, based on certain mathematical algorithms developed using a numerical computing environments like MATLAB is called as ‘Artificial Neural Network’ (ANN). High-performance concrete is a highly complex material, which makes modeling its behavior, a very difficult task. In this present paper, ANN predicting the compressive strength cubes for binary and ternary combination mixes of high performance concrete are developed at the age of 28, 56, 90 and 180 days of curing. For building these models, training and testing using the available experimental results, for 60 specimens produced with 5 different mixture proportions are used. The data used in the multi-layer feed forward neural network models are designed, in a format of eight input parameters covering the age of the specimen, cement, silica fume (SF), fine aggregate (FA), bottom ash (BA), coarse aggregate (CA), steel slag aggregate (SSA) and water. According to these input parameters, in the multi-layer feed forward neural network models are used, to predict the compressive strength values of concrete. It is shown that, neural networks had high potential for predicting the compressive strength results of the high performance concrete, incorporating with silica fume, bottom ash and steel slag aggregate.

KEYWORDS: Silica Fume, Bottom Ash, Steel Slag Aggregate, High Performance Concrete, Artificial Neural Network

INTRODUCTION

High performance concrete is defined as the concrete with improved constructability, improved durability and mechanical properties. The term, high performance means high strength and low permeability. According to ACI definition, concrete which meets the special performance and uniformity requirements that cannot always be achieved routinely by using only conventional materials. Use of chemical admixtures reduces the water content, thereby reducing the porosity within the hydrated cement paste. Mineral admixtures, also called as cement replacement materials, act as pozzolanic materials as well as fine fillers, thereby the microstructure of the hardened cement matrix becomes denser and stronger. Silica fume improves the properties by pozzolanic reaction and by reactive filler effect. It contains a very high percentage of amorphous silicon dioxide, which reacts with large quantity of $Ca(OH)_2$, produced during hydration of cement to form calcium silicate hydrate (CSH) gel. Materials selection will play a large part in the improved concrete of the new century. Industrial by-products such as silica fume, bottom ash and steel slag aggregate improve the engineering and performance properties of high performance concrete, when they are used as a mineral additive or as a partial raw material replacement. A "new" computational paradigm, called neural networks, provides a fundamentally different approach to the derivation and representation of material behavior relationships. In recent years, in many countries, industrial by-products are used for producing high performance concrete incorporating with supplementary cementitious materials. These pozzolanic admixtures are utilized for reducing the cement content in mortar and concrete production.

In this study, groups of specimen with 5 different mixes have been obtained. It has been designed that, the water-binder ratio are 0.45 for the all groups of mixes, respectively. Each group included 5 mixes with binary and a ternary combination of replacement of raw materials of cement, fine aggregate, and coarse aggregate with silica fume (SF), bottom ash (BA) and steel slag aggregate (SSA). In the last years, ANN technology, a sub-field of artificial intelligence, are being used to solve a wide variety of problems in civil engineering applications. The most important property of ANN in civil engineering problems, is their capability of learning directly from examples. The other important properties of ANN are their correct or nearly correct response, to incomplete tasks, their extraction of information from noisy or poor data, and their production of generalized results from the novel cases. The basic strategy for developing an ANN system based models, for material behavior is to train an ANN system on the results of a series of experiments using that material. If the experimental results include the relevant information, about the material behavior, then the trained ANN system will contain enough information about material’s behavior, to qualify as a material model. Such a trained ANN system not only would be able to reproduce the experimental results, but also they would be able to approximate the results in other experiments, through their generalization capability. The aim of this study is to build models, which have different architectures in ANN system, to evaluate the effect of industrial by-products on the compressive strength of concrete.

ARTIFICIAL NEURAL NETWORK

An Artificial Neural Network is an Artificial Intelligence technique. It is a massively distributed processor, made up of the interconnection of simple processing elements, i.e. neuron outputs are connected, through weights, to all others including themselves. The objective is to apply neural network concept, in creating an intelligent system for finding the compressive strength of concrete cubes of different materials of SF, BA, SSA, and conventional concrete for 28, 56, 90 and 180 curing days. The input patterns are chosen according to different types of concrete used with different quantities of admixture and industrial by-product materials. Hence, the input patterns were taken as the age of specimen, Cement, Fine aggregate, Coarse aggregate, Silica fume, Bottom ash, Steel slag aggregate, Water-cement ratio, observed compressive strength. A Neural network modelling was carried out, to predict the strength properties of the conventional concrete, Silica fume concrete (SFC), Bottom ash concrete (BAC). These were aimed at demonstrating the possibilities of using artificial neural network, for predicting the compressive strength of cubes and were compared with the experimental results.

NEURAL NETWORK MODEL

Table 1

Variables	Data Used in Training and Testing the Models	
	Minimum	Maximum
Input Variable		
Age of specimen (Day)	28	28
Cement (kg/m^3)	306.40	383
Silica fume (kg/m^3)	19.15	76.6
Fine aggregate (kg/m^3)	327.5	655

Table 1: Contd.,		
Variables	**Data Used in Training and Testing the Models**	
	Minimum	**Maximum**
Bottom ash (kg/m^3)	65.5	327.5
Coarse aggregate (kg/m^3)	600	1200
Steel slag aggregate (kg/m^3)	120	600
Water (l)	172.4	172.4
Output variable		
Compressive strength for CC	30.1600	34.7950
Compressive strength for SFC	31.9505	36.4220
Compressive strength for BAC	29.4102	35.3212
Compressive strength for SSAC	31.3905	39.5517

Note: CC – Conventional Concrete, SFC – Silica Fume Concrete, BAC – Bottom Ash Concrete, SSAC – Steel Slag Aggregate Concrete

Table 2: Values of Parameters Used In Models for Finding Compressive Strength (Single Combination)

Parameters	ANN
Number of input layer neurons	8
Number of hidden layer	1
Number of first hidden layer neurons	10
Number of second hidden layer neurons	20
Number of output layer neurons	1
Momentum rate	0.7
Learning rate	0.3
Error after learning	0.00100
Learning cycle	4000

The training procedure was carried out, by presenting the network with the set of experimental data in a patterned format. Each training pattern includes an input set of eight parameters, representing age of concrete, cement, fine aggregate, coarse aggregate, silica fume, bottom ash and steel slag aggregate and water; and a corresponding output set representing the compressive strength of concrete cubes. Totally forty five cubes were cast, for finding the compressive strength of single combination. The curing period for a single combination of Model I had 28 days, for finding compressive strength. The curing period for binary and ternary combination had 28, 56, 90 and 180 curing days, for finding compressive strength. In this study, 4000 training cycles have been obtained to minimize the error and to reach the goal point.

RESULTS AND DISCUSSIONS

The figure 1 shows that, the comparison between experimental and predicted ANN values of compressive strength of cubes. The comparison of these values shows that, the neural network modelling is supported better than the experimental results. It is shown that, although the use of the models is not as simple as that of the basic formula, they provide a more accurate tool for the prediction of the concrete strength. The experimental and predicted values can be represented, in terms of the empirical relationship as shown in regression equation 1.

$$y = 0.978\, x + 0.906 \quad \textbf{(1)}$$

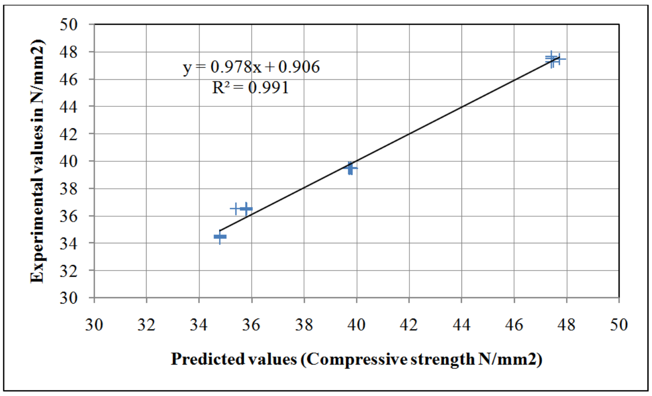

Figure 1: Comparison of Predicted Vs Experimental Values of CC Concrete

Compressive Strength of SFC Concrete Cubes

The figure 2 shows that, the comparison between experimental and predicted ANN values of compressive strength of cubes. The comparison of these values shows that, the neural network modelling is supported better than the experimental results. The experimental and predicted values can be represented in terms of the empirical relationship, as shown in regression equation 2.

$$y = 0.713\,x + 9.648 \tag{2}$$

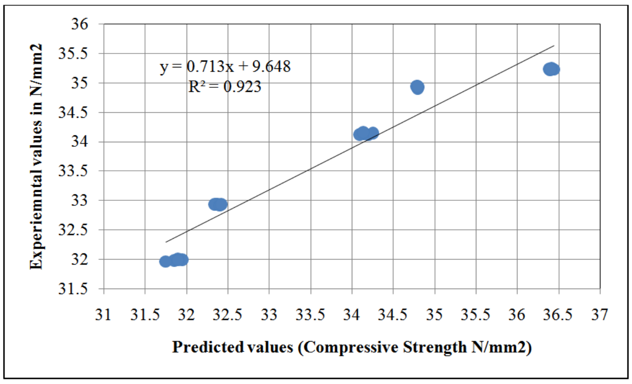

Figure 2: Comparison of Predicted Vs Experimental Values of SFC Concrete

Compressive Strength of BAC Concrete Cubes

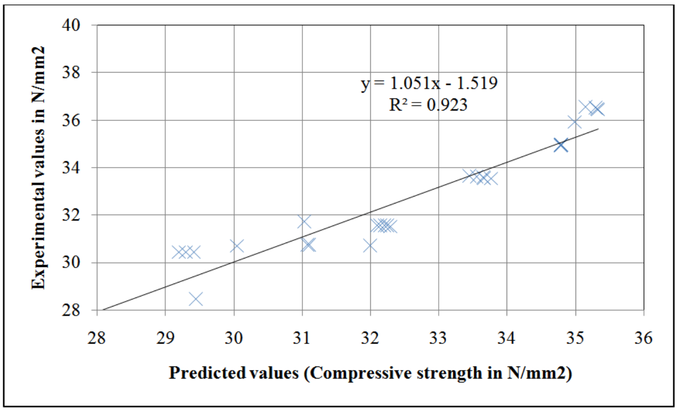

Figure 3: Comparison of Predicted Vs Experimental Values of BAC Concrete

The figure 3 shows that, the comparison between experimental and predicted ANN values of compressive strength of cubes. The comparison of these values shows that, the neural network modelling is supported better than the experimental results. The experimental and predicted values can be represented in terms of the empirical relationship, as shown in regression equation 3.

$$y = 1.051\,x - 1.519 \qquad \textbf{(3)}$$

Compressive Strength of SSAC Concrete Cubes

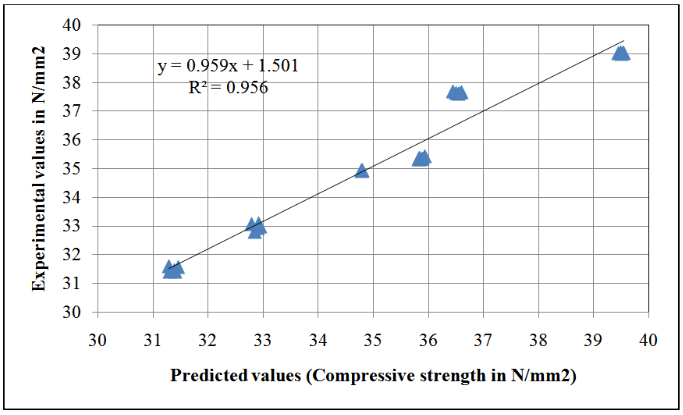

Figure 4: Comparison of Predicted Vs Experimental Values of SSAC Concrete

The figure 4 shows that, the comparison between experimental and predicted ANN values of compressive strength of cubes. The comparison of these values shows that, the neural network modelling is supported better than the experimental results. The experimental and predicted values can be represented in terms of the empirical relationship, as shown in regression equation 4.

$$y = 0.959\,x + 1.501 \qquad \textbf{(4)}$$

Overall Performance of Single Combination

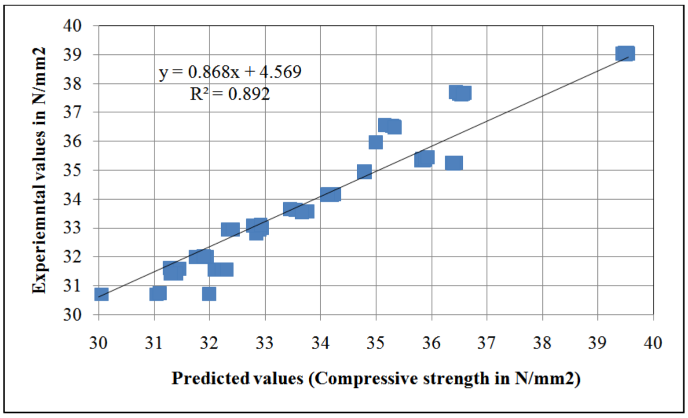

Figure 5: Comparison of Predicted Vs Experimental Values of Overall Mixes

The overall performance of CC, SFC, BAC, and SSAC concrete mixes under ANN modeling, is shown in figure 6. The graph between output and targets, gives the values of R as 0.892 and linear fit of output. The performance of training, validation and testing values is $0.8364e^{-05}$. To train the network, the weights of connections are modified according to the information.. The experimental and predicted values can be represented, in terms of the empirical relationship, as shown in regression equation 5.

$$y = 0.868\,x + 4.569 \quad \textbf{(5)}$$

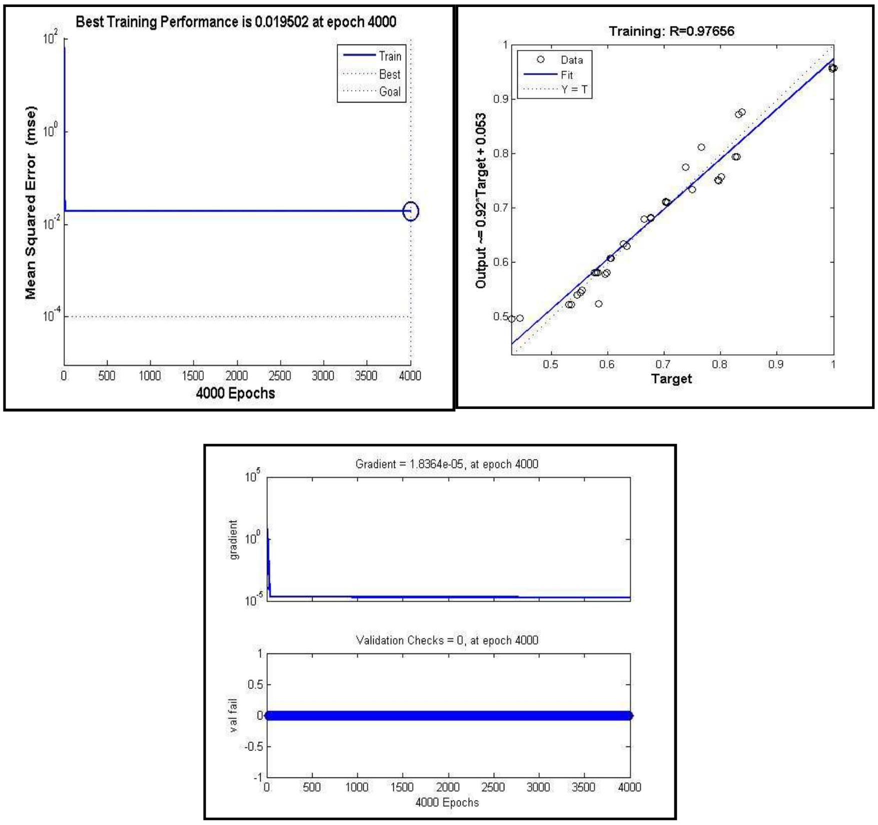

Figure 6: Overall Performances, Training Graph and Validation of Test Values

The network leans by comparing its output for each input pattern, and then calculating the error and propagating an error function backward, through the network. To run the network after it is trained, the values for the input parameters for the project are presented to the network. The process for running the network is extremely rapid, because of a system of coefficient determination R^2 is adopted. The equation of training outputs is A = 0.92 (T) + 0.053 and its R value is 0.97656.

Table 3: Testing Data Sets for Comparison of Experimental and ANN

Data Used in Models Construction										Compressive Strength (Mpa)	
Mix Name	% replace	Age	Cement	FA	CA	SF	BA	SSA	Experimental Results	Predicted Results	% Error
CC	0	28	383	655	1200	0	0	0	34.795	34.926	-0.375
SFC1	5	28	363.85	655	1200	19.15	0	0	36.42	35.239	3.3514
SFC2	10	28	344.7	655	1200	38.3	0	0	34.15	34.130	0.0586
SFC3	15	28	325.55	655	1200.1	57.45	0	0	32.38	32.927	-1.661
SFC4	20	28	306.4	655.3	1199.5	76.6	0	0	31.95	31.980	-0.094
BAC1	10	28	383	589.5	1200	0	65.5	0	35.32	36.486	-3.196
BAC2	20	28	383	524	1200	0	131	0	33.66	33.560	0.298
BAC3	30	28	383	458.5	1201	0	196.5	0	32.15	31.532	1.9599
BAC4	40	28	383	393	1200.1	0	262	0	31.04	30.708	1.0812
BAC5	50	28	383.5	327.5	1200	0	327.5	0	29.41	30.450	-3.415
SSA1	10	28	383.2	655	1080	0	0	120	39.55	39.025	1.3453
SSA2	20	28	383	655	953	0	0	241	36.55	37.605	-2.805
SSA3	30	28	383	654	840	0	0	360	35.86	35.317	1.5375
SSA4	40	28	383	655	720	0	0	480	32.95	32.974	-0.073
SSA5	50	28	383	655	600	0	0	600	31.39	31.463	-0.232

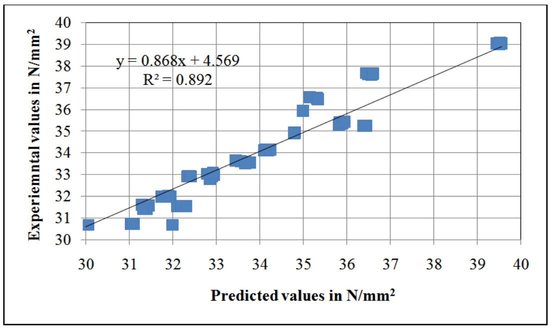

Figure 7: Comparison of Experimental Vs Predicted Values of All Mixes (Single Combination)

The performance of training, validation and testing values is $1.8364e^{-05}$. To train the network, the weights of connections are modified, according to the information. The experimental and predicted values can be represented, in terms of the empirical relationship is shown in regression equation 6.

$$y = 0.868\,x + 4.569 \tag{6}$$

The network leans by comparing its output for each input pattern, and then calculating the error and propagating an error function backward, through the network. To run the network after it is trained, the values for the input parameters for the project are presented to the network. The process for running the network is extremely rapid because, the system of coefficient determination R^2 is adopted. The equation of training outputs is A = 0.92 (T) + 0.053 and its R value is 0.97656.

CONCLUSIONS

This paper discussed the importance of analytical investigation, by using Artificial Neural Network (ANN) modeling, for predicting compressive strength, durability studies and flexural behaviour of high performance concrete specimens. This study demonstrated that, multi layer feed forward artificial neural networks are pragmatic methods, for predicting compressive strength values of conventional concrete and high performance concrete, for a single combination of high performance concrete beams with tiny error rates. Artificial neural networks are capable of learning and generalizing, from examples and experiences. This makes artificial neural networks, a powerful tool for solving some of the complicated civil engineering problems. In this study, using these beneficial properties of artificial neural networks, in order to predict the 28 days compressive strength of high performance concrete containing silica fume, bottom ash and steel slag aggregate, were developed with two different multilayer artificial neural network architectures. An ANN model was developed, to predict the various strength parameters and the predicted values were compared with the experimental results. Finally, the results found that, the experimental and analytical investigations indicated that, the results are harmonious.

REFERENCES

1. Abul, K. Azad, and Ibrahim, Y. Hakeem., (2013), Flexural behaviour of hybrid concrete beams reinforced with ultra-high performance concrete bars, *Construction and Building Materials*, Vol.49, pp.128-133.

2. Adriana Trocoli Abdon Danta, Monica Batista Leite, and Koji de Jesus Nagahama., (2013), Prediction of compressive strength of concrete containing construction and demolition waste using artificial neural network, *Construction and Building Materials*, Vol. 38, pp. 717-722.

3. Aggarwal, P., Aggarwal, Y., and Gupta, S.M., (2007), Effect of Bottom ash as replacement of Fine aggregates in concrete, *Asian Journal of Civil Engineering (Building and Housing)*, Vol.08, No. 01, pp. 49-62.

4. Agarwal, V., and Sharma, A., (2010), Prediction of slump in concrete using Artificial Neural Networks, World Academy Science, *Engineering and Technology*, Vol.04, No. 09, pp.279-286.

5. Ahmed, S. Ouda., (2015), Development of high-performance, heavy density concrete using different aggregates for gamma-ray shielding, *Progress in Nuclear Energy*, Vol.79, pp. 48-55.

6. Aitcin, P.C., (2003), The durability characteristics of high performance concrete: a review, *Cement and concrete composites*, Vol.25, pp. 409-520.

7. Chore, H.S., and Joshi, M.P., (2015), Multiple regression models for prediction of compressive strength of concrete comprising industrial waste products, *The Indian Concrete Journal*, Vol.89, Issue 09, pp. 33-46.

8. DalilaBenamara, BouzidiMezghiche and MechroughFatma Zohra., (2014), The deformability of a high performance concrete (HPC), *Physics Procedia, Eights International conference on Material sciences*, CSM-ISM5, Vol.55, pp. 342-347.

9. Deepa, C., SathiyaKumari, S., and Preamsudha, V., (2010), Prediction of the compressive strength of high performance concrete mix using tree based modelling, *International Journal of Computer Applications*, Vol.06, No.05, pp. 18-24.

10. Deepak, M., and Ramakrishnan, K., (2015), ANN is modelling for prediction of compressive strength of concrete having silica fume and metakaolin, *International Journal of ChemTech Research*, Vol.08, No.01, pp. 184-189.

11. Hadi, M.N.S., (2008), Flexural Behaviour of high strength concrete beams with confining reinforcement, *ICCBT*, Vol.03, pp.35-48.

12. Hemalatha, T., Hari Hara Sudhan and Nagesh, R. Iyer., (2016), Prediction of long term compressive strength of concrete made with supplementary cementitious material through regression analysis, *The Indian Concrete Journal*, Vol.90, pp. 49-58.

13. Hodhod, O.A., and Ahmed, H.I., (2013), Developing an artificial neural network model to evaluate chloride diffusivity in high performance concrete, *HBRC Journal*, Vol.09, pp. 15-21.

14. Huang Yi, Guoping Xu, Huigao Cheng, Junshi Wang, Yinfeng Wan, and Hui Chen., (2012), An overview of utilization of steel slag, *Procedia Engineering*, Vol.16, pp.791-801.

15. Indian Standard – *Specification for 43 grades Ordinary Portland cement to* IS 8112-2013, Bureau of Indian Standards, New Delhi, 2013.

16. L. Himaja & V. M. Naidu, Study on Establishing Relationship between Per Capita Trip Rate with Demand Variables using Artificial Neural Networks, TJPRC:International Journal of Traffic and Transportation Engineering & Research, Volume 2, Issue 1, July-Decemeber 2017, pp.1-12

17. Indian Standard - *Silica Fume – Specification to IS 15388-2003,* Bureau of Indian Standards, New Delhi, 2003.

18. Indian Standard – *Specification for Coarse and Fine Aggregates from Natural Sources for concrete to IS 383-1970,* Bureau of Indian Standards, New Delhi, 1971.
19. Indian Standard – *Methods of Test for Aggregates for Concrete to IS 2386-1963,* Bureau of Indian Standards, New Delhi, 2003.
20. Indian Standard – *Concrete Admixtures – Specification to IS 9103-1999,* Bureau of Indian Standards, New Delhi, 1999.
21. Indian Standard - *Methods of Test for Strength of Concrete* to *IS 516-1959,* Bureau of Indian Standards, New Delhi, 2002.
22. Indian Standard – *Non-Destructive Testing of Concrete – Methods of Test, 13311-1992 (Part – I to IV)* Bureau of Indian Standards, New Delhi, 1992.