Chemical Science Review and Letters ISSN 2278-6783

Research Article

Compressive Strength Modelling of Geopolymer Concrete Incorporated with M-Sand and Bottom Ash - A Neural Network Approach

Rajagopal Shanmugam*

Department of Civil Engineering, Muthayammal Engineering College, Rasipuram, Namakkal District, Tamil Nadu

Abstract

The Compressive strength of concrete is considered as one of the key factors for quality assurance of concrete. In this study a data-driven model, i.e., Artificial Neural Network (ANN) was used to predict the 28 days compressive strength of m-sand and bottom ash incorporated geo-polymer concrete. Recovered bottom ash as fine aggregate is the current need of the hour owing to its environmental friendly aspect of re-using the wastes for construction. The ANN model was constructed using experimental data and the data gathered from literature. Totally 70 set of data were used for ANN modelling, 80% in the training phase, 10% in testing phase and remaining 10% for validation phase. To construct the model, 6 input parameters were used to attain one output parameter. Compressive strength of geo-polymer concrete containing m-sand and bottom ash was considered as output. The results obtained in the training, testing and validation phases strongly show the potential use of ANN to predict 28 days compressive strength of concretes containing m-sand and bottom ash.

Keywords: Geo-polymer concrete, m-sand, bottom ash, compressive strength, ANN model

***Correspondence**
Author: Rajagopal Shanmugam
Email: shanmugamrsp@gmail.com

Introduction

Geopolymer concrete mix is a composition of synthetic alumino silicate material.Geopolymer concrete have excellent mechanical and durability properties including acid, fire resistance and good heat resistance properties [1, 2]. Geopolymerric materials are synthesized by several materials like rice husk bark ash [3], fly ash [4-6], mine waste mud, slags, Even though several materials are used as a source, fly ash is considered as a main alumino-silicate source for high strength achievement [7-9]. Many researchers reported that, higher compressive strength is achieved in fly-ash based geopolymer concrete if it is added with large quantity of sodium-based alkali activating solution. Better mechanical properties with respect to higher volume of geopolymeric gel at nominal density results in homogenous microstructure. The microstructure formation of fly-ash based geopolymer concrete is based on the chemical processes occur in the solution phase. In this study bottom ash was used as fine aggregate in fly ash based geopolymer concrete [10-13].

Compressive strength of geopolymer concrete depends on various factors. Since compressive strength prediction of geopolymer concrete is complex in nature, artificial neural network (ANN) is a useful technology to find the solution for this complex problem by cooperating highly interconnected computing elements called neurons [14]. The major advantage of ANN is, it has the capability of learning from the examples. Another advantage of ANN is, it will response to incomplete tasks and retrieve information from lesser data also. These advantages make ANN as a powerful tool to solve complex engineering problems, mainly, if data are complex or in sufficient [15, 16]. The basic approach in developing ANN based models is to train ANN systems with data obtained from the experiments. If relevant information is obtained, then the trained ANN systems will be considered as a qualified model to assess the behavior of materials. Such systems not only able to replicate the experimental results, but also they can able to approximate the results of other experiments through their capability [17].

Several studies has been carried out to predict the compressive strength of concrete using ANN. For example, Kamalloo etal. and [18] developed an ANN model for prediction of compressive strength of silica fume added concrete. Fazel et.al [19, 20] used ANN model for assessing the compressive strength of fly ash concrete. The previous work of several researchers shows that the application of ANN for predicting the properties of geo polymer concrete is limited based on the applications [21, 22]. Owning to limited research existence in prediction of geopolymer concrete properties by soft-computing tools, this study aims to develop a suitable ANN models for predicting the compressive strength of fly ash based geopolymers incorporated with bottom ash and m-sand.

Data Collection

The network is trained with input data obtained from several experimentations related to geopolymer concrete, input-data values were gathered from previous works [23]. The collected data contain various mix proportions and sources of the constituent ingredients. Besides, a similarity between the data was considered and confirmed that they are source materials of aluminosilicate. The series of data, totally 70 set of data, related to the compressive strength of geopolymer specimens made from fly ash, bottom ash and m-sand were collected from literatures and experimentation to train the network. The detailed mix proportion of geopolymer mixes are furnished in **Table 1**. M denotes mix of geopolymer concrete comprising several ingredients in different proportions. On trial basis the maximum molarity is found as 12. Hence, the optimal mix is adopted in preparation of geopolymer concrete and used for inputs of neural network.

Table 1 Mix proportions of geopolymer concrete considered as input in Neural Network system

Mix ID	Fly ash in kg/m^3	Sand in kg/m^3	M-sand in kg/m^3	Bottom ash in kg/m^3	Coarse aggregate in kg/m^3	Water in kg/m^3	NaOH in kg/m^3	Na_2SiO_3 in kg/m^3	Compressive Strength (MPa)
M-1	455	635.4	0	0	1249.5	36.5	58.8	145	16
M-2	480.7	585.4	0	0	1118	44.2	63.5	163.1	21.3
M-3	480.2	620.5	0	0	1108	44.2	63.5	163.1	21.5
M-4	554.7	560.4	0	0	1002.2	14.2	68.8	170	21
M-5	543.7	535.4	0	0	987.5	28.3	72.2	180.5	23
M-6	585.6	535.4	0	0	832.8	28.3	72.2	180.5	20
M-7	554.7	450	0	0	929.1	14.2	74.8	184.6	23
M-8	585.6	576	0	0	1018	12.7	78	200.5	25
M-9	552.6	567.8	0	0	987.5	44.2	78	190.5	22
M-10	555	550.8	0	0	957.9	44.2	68.5	171.1	23
M-11	638.2	534.2	0	0	929.1	44.2	68.5	171.1	23
M-12	510.7	567.1	0	0	882.2	28.3	68.5	171.1	24
M-13	585.6	586	0	0	907.5	28.3	79.8	204.6	24
M-14	483.7	585.4	0	0	1018	28.3	70.2	175.5	23
M-15	554.7	535.4	0	0	832.8	14.2	73	180.3	23.5
M-16	583.7	535.4	0	0	882.2	14.2	73	180.3	33
M-17	564.7	543.2	0	0	832.8	14.2	73.8	185.6	30
M-18	585.6	515.2	0	0	902	14.2	73.8	185.6	33
M-19	584.7	535	0	0	798.2	28.3	80.8	204	30
M-20	585.6	534.6	0	0	883	12.7	80.8	204	35
M-21	570.8	535	0	0	883	28.3	78.24	195.6	33
M-22	547	567.1	0	0	957.9	44.2	68.5	171.1	33
M-23	585.6	535.4	0	0	832.8	12.7	82	210.5	34
M-24	564.7	535.4	0	0	832.8	28.3	82.2	205.5	35
M-25	519.7	613	0	0	964	44.2	68.5	171.1	36
M-26	585	550.8	0	0	907.5	14.2	82.8	210.6	37
M-27	585	585.4	0	0	1018	28.3	82.8	210.6	37
M-28	585	567.1	0	0	957.9	14.2	83	207.3	39
M-29	638.2	545	0	0	882.2	12.7	68.5	171.1	38
M-30	485.6	613	0	0	1218	58.5	65	167.3	18
M-31	455	1249.5	613	0	36.5	58.8	145	145	18
M-32	480.7	1118	608.1	0	44.2	63.5	163.1	163.1	23
M-33	480.2	1108	610	0	44.2	63.5	163.1	163.1	23
M-34	554.7	1002.2	589.9	0	14.2	68.8	170	170	22
M-35	543.7	987.5	615.6	0	28.3	72.2	180.5	180.5	21
M-36	585.6	832.8	572.2	0	28.3	72.2	180.5	180.5	20
M-37	554.7	929.1	613	0	14.2	74.8	184.6	184.6	22
M-38	585.6	1018	670.8	0	12.7	78	200.5	200.5	24.5
M-39	552.6	987.5	589.9	0	44.2	78	190.5	190.5	25
M-40	555	957.9	572.2	0	44.2	68.5	171.1	171.1	29

M-41	638.2	929.1	615.6	0	44.2	68.5	171.1	171.1	29
M-42	510.7	882.2	652.1	0	28.3	68.5	171.1	171.1	25
M-43	585.6	907.5	670.8	0	28.3	79.8	204.6	204.6	25
M-44	483.7	1018	572.2	0	28.3	70.2	175.5	175.5	26
M-45	554.7	832.8	613	0	14.2	73	180.3	180.3	26
M-46	583.7	882.2	652.1	0	14.2	73	180.3	180.3	30
M-47	564.7	832.8	615.6	0	14.2	73.8	185.6	185.6	31
M-48	585.6	902	589.9	0	14.2	73.8	185.6	185.6	32
M-49	584.7	798.2	572.2	0	28.3	80.8	204.6	204	30
M-50	585.6	883	670.8	0	12.7	80.8	204.6	204	32
M-51	570.8	883	572.2	0	28.3	78.24	195.6	195.6	26
M-52	547	957.9	608.1	0	44.2	68.5	171.1	171.1	26
M-53	585.6	832.8	615.6	0	12.7	82	210.5	210.5	38
M-54	564.7	832.8	615.6	0	28.3	82.2	205.5	205.5	36
M-55	519.7	964	625.7	0	44.2	68.5	171.1	171.1	37
M-56	585	907.5	572.2	0	14.2	82.8	210.6	210.6	36
M-57	585	1018	550.1	0	28.3	82.8	210.6	210.6	39
M-58	585	957.9	572.2	0	14.2	83	207.3	207.3	37
M-59	638.2	882.2	613	0	12.7	68.5	171.1	171.1	38
M-60	485.6	1218	713	0	14.2	65	167.3	167.3	18
M-61	405	0	136.6	0	28.3	108.35	70.88	70.88	35.93
M-62	405	0	273.3	0	44.2	108.35	70.88	70.88	37.46
M-63	405	0	409.9	0	12.7	108.35	70.88	70.88	33.63
M-64	405	0	546.5	0	28.3	108.35	70.88	70.88	31.9
M-65	405	0	683.1	0	44.2	108.35	70.88	70.88	27.26
M-66	405	0	0	68.31	14.2	108.35	70.88	70.88	34.73
M-67	405	0	0	136.62	28.3	108.35	70.88	70.88	35.6
M-68	405	0	0	204.93	14.2	108.35	70.88	70.88	36.2
M-69	405	0	0	273.24	12.7	108.35	70.88	70.88	36.7
M-70	405	0	0	341.55	14.2	108.35	70.88	70.88	34.5

Development of Neural Network model

There are different neural network architectures are in vogue, therefore it is essential to consider the following principles for selection of suitable neural network.

- Number of input nodes of the neural network is selected based on the total number of independent variables.
- Number of hidden nodes is fixed based on 80% of the input nodes.
- Besides, to avoid longer training period, hidden layers should be reduced.
- Number of neurons fixed should be adequate for the network to avoid overstating (2).
- Input data for 1-30sets are Fly ash, sand, Coarse aggregate,water,NaOH,Na_2SiO_3
- Input data for 31-60sets are Fly ash, M.sand, Coarse aggregate,water,NaOH,Na_2SiO_3
- Input data for 61-65sets are Fly ash, M.sand, Coarse aggregate,water,NaOH,Na_2SiO_3
- Input data for 66-70sets are Fly ash, Bottom Ash, Coarse aggregate,water,NaOH,Na_2SiO_3
- Output data is Compressive strength for all 70 sets.

By and large, back-propagation is the prevalent method for training the neural network. MATLAB software was used to train the network. Owing to its user friendliness, MATLAB was chosen to train the network. Levenberg-Marquardt algorithm was adopted to train the neural network. Besides, a single layer feed-forward neural network system was developed. The performance of the network was analysed based on R^2 and Mean Absolute Percentage Error (MAPE) value. Fundamentally neural network comprises of three layers namely input, hidden and output layer. Hidden layer is linked with other layers by weights, bias and activation functions. Each layer consists of numerous neurons. Each neuron gain input from the data set. Weighted inputs are collectively processed by an activation function there by output is produced. The structure of ANN model is shown in **Figure 1**.

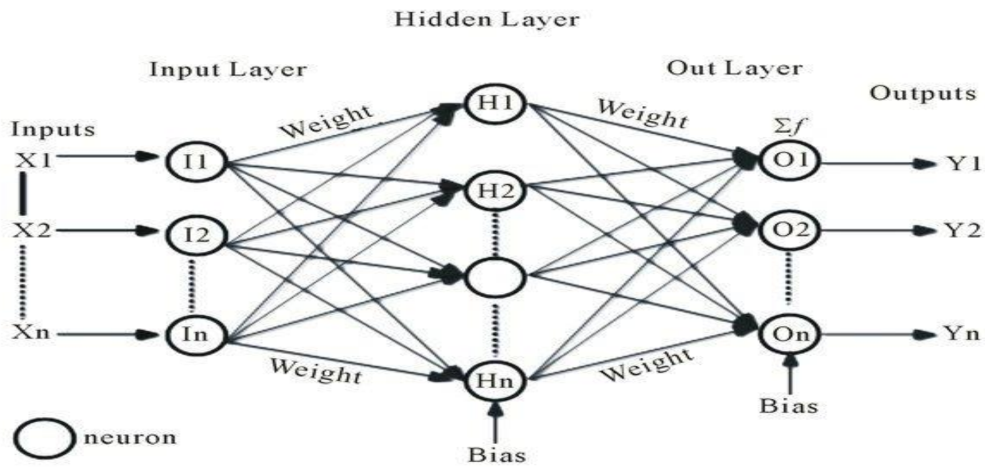


Figure 1 Structure of ANN model

Training and testing of neural network

The developed neural network model includes an input layer with 6 nodes, hidden layer with 12 nodes and an output layer with 1 node. Normally, one hidden-layer is preferred in the neural network model for most of the applications. Trial and error is required to sustain the accuracy in designing the neural network architecture. The neural network was trialled with four, eight, ten and twelve hidden nodes. Out of these trials, the best performance was obtained in the neural network comprising twelve hidden nodes associated value of MAPE. The structure of the developed ANN model in MATLAB is shown in **Figure 2**.

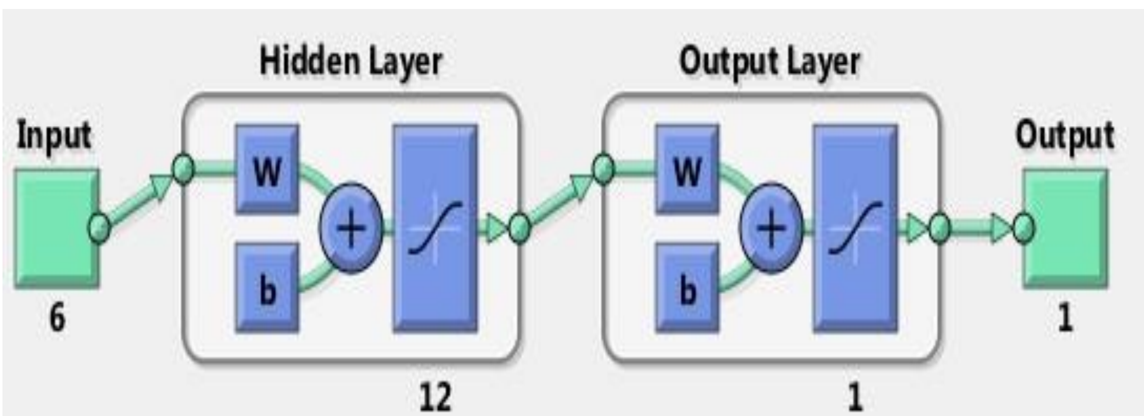


Figure 2 Structure of developed ANN model in MATLAB

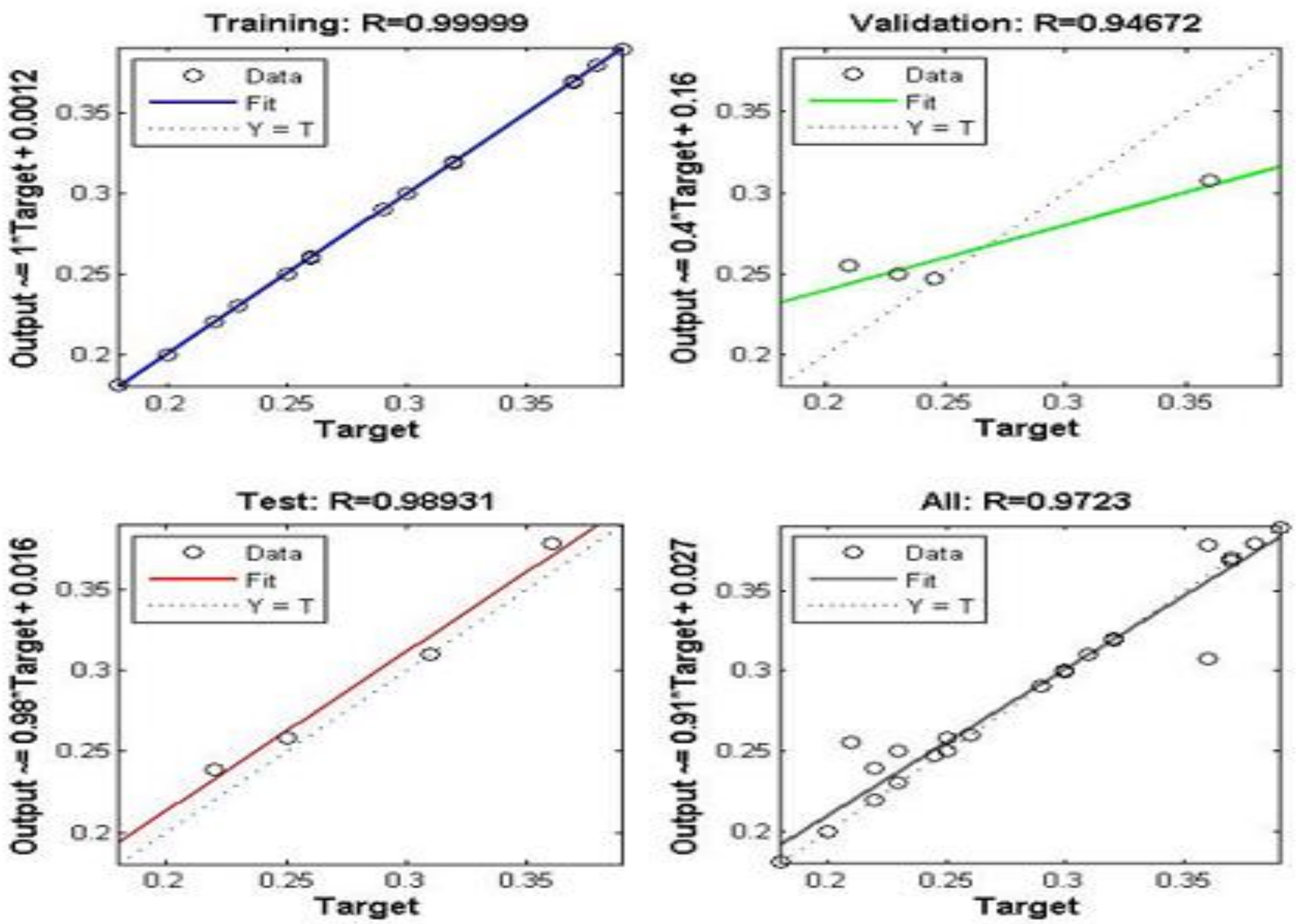
The neural network was specifically trained to suit inputs and the targeted output. However, if generalization is improved obviously network stops training. It can be ensured with an increase in value of mean squared error (MSE). Mean squared error (R) is an average squared difference between input and the targeted output. The value of R shows the correlation among the output and targets.

The mean squared error is calculated from the following equation

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2$$

Where, N is the number of data used, t_i are the output values and a_i are the target values. The regression plot of the network for training, testing and validation is shown in **Figure 3**.

Based on the R value the error is calculated, if the value of R is zero that means no error. If R value is 1, then the correlation between targeted output and output obtained by neural fitting tool is very closer. 10% of the data were considered for testing and R value of 0.989 was obtained for testing. R value of 0.946 was obtained for testing. The overall status of the network is shown in figure 4.Lower MSE and R value indicating the best performance of neural network model. Several trials were carried out by varying number of neurons and the best result was obtained at 7^{th}epochs contains single hidden layer with 12 neurons.



.

Figure 3 The regression plot of the network for training, testing and validation

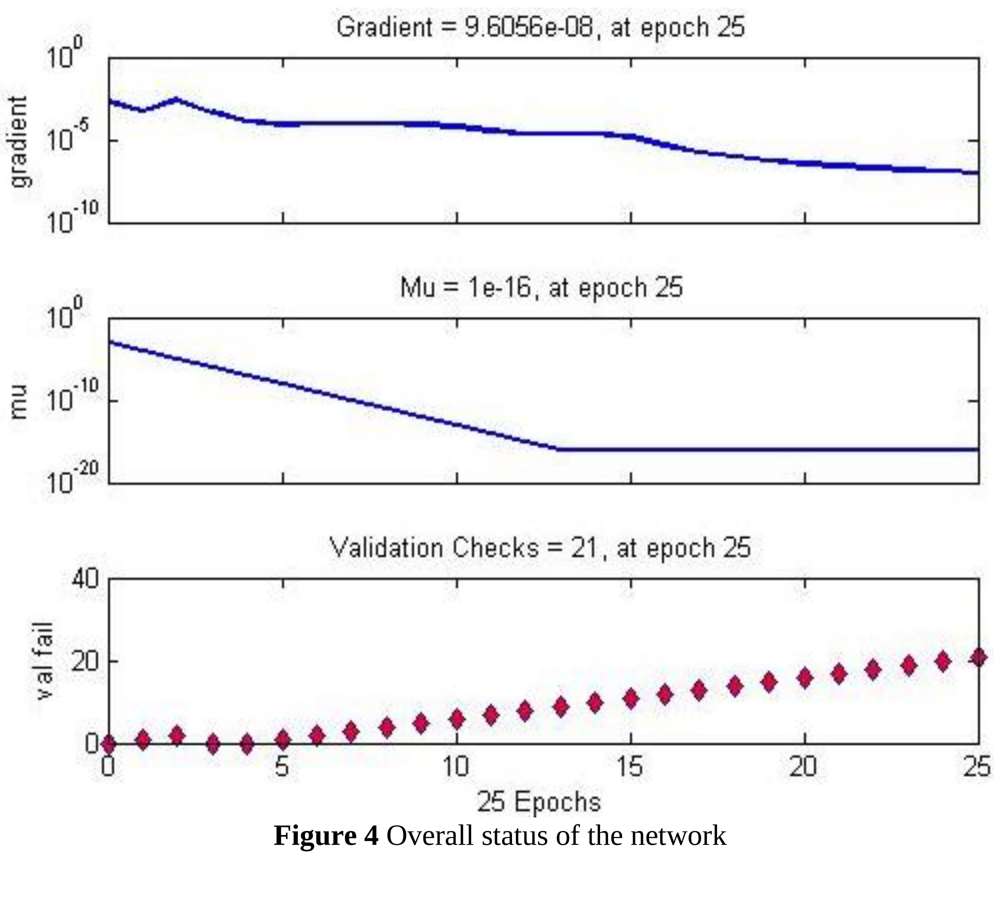


Figure 4 Overall status of the network

Validation of ANN model

The developed ANN model is validated by corroborating with the experimental results of different mix proportions. The 28 days compressive of geopolymer concrete were tested and compared with the results obtained from the ANN model. The percentage deviation between experimental result and results predicted through ANN model is noted. The percentage error was calculated between the test values and the predicted values through ANN model are presented in **Table 2**.

Table 2 The percentage error was calculated between the test values and the predicted values through ANN model

Mix ID	Compressive Strength (MPa)		% Error
	Experimental result	ANN predicted result	
M-1	16	17.2	0.93
M-2	21.3	19.6	1.09
M-3	21.5	20.7	1.04
M-4	21	21.3	0.99
M-5	23	22.3	1.03
M-6	20	19.6	1.02
M-7	23	21.7	1.06
M-8	25	24.3	1.03
M-9	22	21.7	1.01
M-10	23	22.4	1.03
M-11	23	23.3	0.99
M-12	24	22.8	1.05
M-13	24	23.6	1.02
M-14	23	21.7	1.06
M-15	23.5	24.1	0.98
M-16	33	32.3	1.02
M-17	30	29.3	1.02
M-18	33	31.4	1.05
M-19	30	29.7	1.01
M-20	35	33.7	1.04
M-21	33	32.1	1.03
M-22	33	34.1	0.97
M-23	34	33.6	1.01
M-24	35	34.3	1.02
M-25	36	35.1	1.03
M-26	37	36.2	1.02
M-27	37	35.8	1.03
M-28	39	38.3	1.02
M-29	38	36.7	1.04
M-30	18	17.2	1.05
M-31	18	18.6	0.97
M-32	23	24.1	0.95
M-33	23	21.7	1.06
M-34	22	21.6	1.02
M-35	21	19.7	1.07
M-36	20	21.3	0.94
M-37	22	20.9	1.05
M-38	24.5	23.8	1.03
M-39	25	24.1	1.04
M-40	29	28.3	1.02
M-41	29	27.7	1.05
M-42	25	24.6	1.02
M-43	25	25.7	0.97
M-44	26	24.8	1.05

M-45	26	25.3	1.03
M-46	30	29	1.03
M-47	31	29.6	1.05
M-48	32	30.7	1.04
M-49	30	29.1	1.03
M-50	32	30.7	1.04
M-51	26	25.5	1.02
M-52	26	24.9	1.04
M-53	38	38.3	0.99
M-54	36	36.5	0.99
M-55	37	36.3	1.02
M-56	36	34.9	1.03
M-57	39	37.9	1.03
M-58	37	36.3	1.02
M-59	38	39	0.97
M-60	18	18.6	0.97
M-61	35.93	36.2	0.99
M-62	37.46	38	0.99
M-63	33.63	33.4	1.01
M-64	31.9	32.6	0.98
M-65	27.26	28.5	0.96
M-66	34.73	35.2	0.99
M-67	35.6	35.1	1.01
M-68	36.2	34.7	1.04
M-69	36.7	37.3	0.98
M-70	34.5	33.9	1.02

Results and Discussions

The data obtained from experimental investigation was considered as output data for ANN model and the target output was specified as the actual compressive strength value obtained from experimental verification. The prediction has been made for each and every individual compressive strength test results using ANN model. The best curve fit equation has been developed to between the predicted strength obtained from ANN model and the actual compressive strength and illustrated in **Figure 5**.

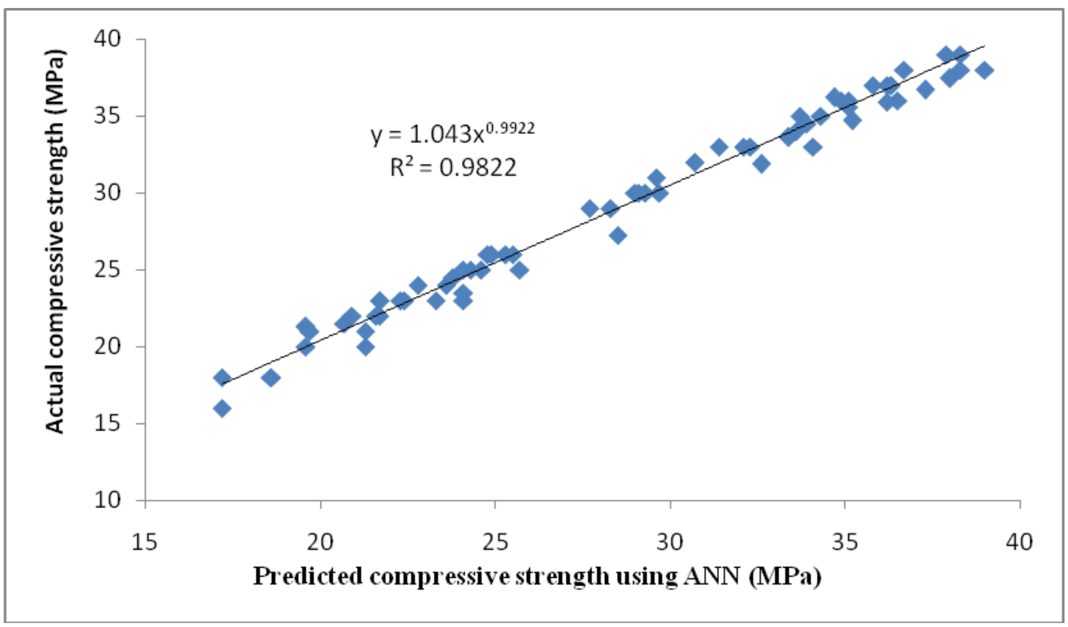


Figure 5 Predicted strength by ANN Vs actual compressive strength

The correlation coefficient of 0.982 was obtained for the best curve fit equation plotted between the predicted strength obtained from ANN model and the actual compressive strength. The coefficient of determination shows the strength prediction is very close to the actual values obtained from the test results. Among numerous techniques to predict the strength of concrete, ANN is considered as the most effective tool predicts the strength of concrete.

In this paper the artificial neural net work modeling done for geopolymer concrete with partial replacement of manufactured sand, bottom ash for river sand. So far the literature available for geopolymer concrete with manufactured sand and river sand in the literature appended as 12 took 55 values but here 70 values were taken for prediction of results. Here the outputs available are more accurate and error is minimized.

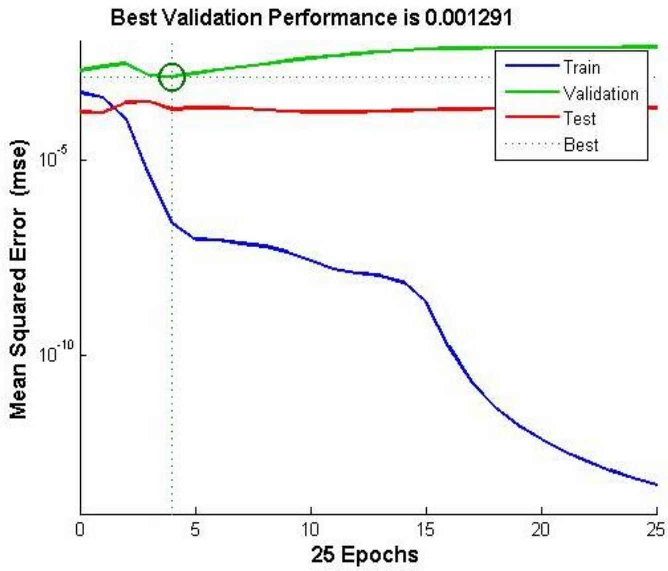


Figure 6 Predicted strength by ANN vs. Actual compressive strength

Conclusion

The test verifications showed that, the compressive strength prediction of geo-polymer concrete comprising m-sand and bottom ash using ANN attained higher accuracy. The accuracy predominantly depends on the learning pattern as well as number of data used in the network for training and testing. The percentage error was calculated from the results obtained from the ANN model. The maximum error is within the range of 0.93 to 1.06 when compared to the values obtained from the experimentation. The level of accuracy indicates that the developed ANN model is dependable to predict the 1ressive strength of the m-sand and bottom ash incorporated geo-polymer concrete. The results obtained from the ANN model for compressive strength prediction showed maximum percentage of error within the range of 0.93 to 1.05 when compared to the experimentally obtained values.

References

[1] Olivia, M H. Nikraz, Properties of fly ash geo polymer concrete designed by Taguchi method, Materials and Design 36 (2012) 191–198.

[2] Wang, M.R D.C. Jia, P.G. He, Y. Zhou, Micro structural and mechanical characterization of fly ash cenosphere /metakaolin-based geo polymeric composites, Ceramics International 37 (2011) 1961–1966.

[3] Oztas¸ A., M. Pala, E.Ozbay, E. Kanca, N. C¸aglar, and M.A. Bhatti, “Predicting the compressive strength and slump of high strength concrete using neural network,” Construction and Building Materials, vol. 20, no. 9, pp. 769–775, 2006

[4] Akkurt.S, G. Tayfur, and S.Can, “Fuzzy logic model for the prediction of cement compressive strength,” Cement and Concrete Research, vol. 34, no. 8, pp. 1429–1433, 2004

[5] Davidovits .J, “Geo polymers : inorganic polymeric new materials’ ,Journal of Thermal Analysis 37 issue8 (1991) 1633-1656

[6] Lee JJ, Kim D, Chang SK, Nocete CFM. An improved application technique of theadaptive probabilistic neural network for predicting concrete strength. Comput Mater Sci 2009;44:988–98

[7] Alshihri.M.M, A. M. Azmy, and M. S. El-Bisy, “Neural net works for predicting compressive strength of structural lightweight concrete,” Construction and Building Materials, vol. 23,no. 6, pp. 2214–2219, 2009

[8] Lai S, Sera M. Concrete strength prediction by means of neural network. Construction Building Materials 1997;volume11,Issue(2):93-98
[9] Saridemir,M "Genetic programming approach for prediction of compressive strength of concretes containing rice husk ash, "Construction and Building Materials, vol. 24, no. 10, pp. 1911–1919, 2010
[10] Baykasoglu, A,T. Dereli, and S. Tanis¸, "Prediction of cement strength using soft computing techniques," Cement and Concrete Research, vol. 34, no. 11, pp. 2083–2090, 2004
[11] Fazel Zarandi MH, Turksen IB, Sobhani J, Ramezanian pour AA. Fuzzy polynomial neural networks for approximation of the compressive strength of concrete. Appl Soft Computing 2008;8:488–98.
[12] HuaXu ,"Fly ash and its use in concrete", The Indian Concrete Journal, April 2003, 975 - 995 60.
[13] Wong .Y. L., Lam . L, Poon C.S, Zhou. F.P, "Properties of fly ash modified cement mortar- aggregate interfaces", Cement and concrete Research 29 (1999) 1905 -1913
[14] Rangan, B.V. "Engineering Properties of Geo polymer Concrete", Chapter 11 in Geo polymers: Structures, Processing, Properties, and Applications, Editors: J.Provis and J. van Deventer, Wood head Publishing Limited, London.(2009
[15] Siddiqui, K.S.,"Strength and Durability of Low-Calcium Fly Ash-based Geopolymer Concrete", Final Year Honours Dissertation, The University of Western Australia, Perth.(2007).
[16] Nazari,N A. Bagheri., S. Riahi, Properties of geo polymer with seeded fly ash and rice husk bark ash, Materials Science and Engineering A 528 (2011) 7395–7401.
[17] Davis, R,E., R. W. Carlson, J. W. Kelly, and A. G. Davis, "Properties of cements and concretes containing fly ash", Proceedings, American Concrete Institute 33:577-612.
[18] Kamalloo,A Y. Ganjkhanlou, S. H. Aboutalebi, and H. Nouranian, "Modeling of compressive strength of Metakaolin based geo polymers by the use of artificial neural network," International Journal of Engineering, vol. 23, no. 2, pp. 145–152, 2010
[19] Hong-Guang N, Ji-Zong W. Prediction of compressive strength of concrete byneural networks. Cem Concr Res 2000;30:1245–50
[20] Davidovits . J., "Geo polymers : Inorganic polymeric new materials", Journal of Materials Education , Vol. 16 ,(1994), pp. 91 – 139
[21] Pacheco-Torgal,FJ.P.Castro-Gomes,S.Jalali,Alkali—activatedbinders: a review .Part1. Historical back ground, terminology, reaction mechanism sand hydration products. Construction and Building Materials 22, 1305–1314
[22] Kumar,S R. Kumar, S.P. Mehrotra, Influence of granulated blast furnace slag on the reaction, structure and properties of fly ash based geo polymer, Journal of Materials Science 45 (2010) 607–615.
[23] Saridemir.M, "Prediction of compressive strength of concretes containing metakaolin and silica fume by artificial neural networks," Advances in Engineering Software, vol. 40, no. 5, pp.350–355, 2009.

Publication History

Received	17.06.2021
Revised	19.10.2021
Accepted	20.11.2021
Online	31.12.2021