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ANN Modelling for Prediction of Compressive Strength of Concrete Having Silica Fume and Metakaolin

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Abstract: Artificial neural networks (ANN) a sub-field of intelligent systems, are widely employed to resolve a diversity of civil engineering problems. In the present paper, using data from literature ANN models (ANN-A, ANN-B & ANN-C) was modelled to predict the compressive strength of concrete, having different mixtures at different age of 1, 3, 7, 28, 56, 90 and 180 days. The model ANN-(A) inspects eight and ANN-(B) & ANN-(C) examines 7 different parameters that comprises: sand (S), metakaolin (MK), superplasticizer (SP) ,aggregate (A) , silica fume (SF), cement, water, and time, respectively. Artificial neural networks take robust prospects for prediction of compressive strength of concretes containing silica fume and metakaolin which is recognized by validation, testing and training results. This strength prediction will aid the cement factories in manufacturing the cement, which when used in concrete will results in required concrete strength
Keywords- Silica fume, artificial neural network, compressive strength, metakaolin.

Introduction

It is accepted that silica fume and metakaolin, are industrial wastes that produce nice variation of properties [1]. In concrete production these pozzolanic admixtures are used for lowering the cement amount [2]. Also, the employment of like metakaolin (MK), silica fume (SF) is critical for manufacturing high performance concrete. In high performance concrete once these constituents, used as mineral admixtures, will increase strength properties of concrete [3, 4] Metakaolin (MK) is got by calcinination of kaolin clay at 700˚C - 850˚C [3, 4, 5, and 6]. Silica fume is a by-product obtained from silicon industries [4]. Metakaolin includes micro filler properties like that of silica fume. Combination of SF and MK results in dense impermeable concrete [7]

Using SF and MK together is currently a normal approach for acquiring high strength concretes. From many researches, it is confirmed that the combination of SF and MK in concrete raise the compressive strength of concrete. Wong and Abdul Razak [8] in their work concluded that concrete specimens prepared with SF and MK had compressive strength larger than that specimens prepared with other mix ratios. Poon et al. [2], also found that concretes manufactured with metakaolin had meaningfully larger compressive strength when matched to strength of concrete comprising silica fume.

The objective of this work is to build Artificial Neural Network models (ANN) namely ANN-(A) which have eight inputs, ANN-(B) & ANN-(C) have seven number of inputs each in artificial neural network system respectively, to judge the impact of metakaolin and silica fume on compressive strength of concrete. To develop these ANN models dataset of one ninety five specimens at 1, 3, 7, 28, 56, 90 and 180 days from technical literature [3, 8] is used.

Neural network models

Artificial neural network are centered on the natural behavior of human nervous system. ANN are tremendously parallel systems consist of various elements which are interlinked by many weights [9, 10]. Usually, ANN consist of input, output layer of neurons, and one or more hidden layer of neurons. All the layers are totally interlinked by various weights. The neurons in the input layer get data from the external surrounding and pass them to hidden layer neurons [11, 12]. Many number of processing units is present in the hidden layer, that is present in between the input and output layer [13].result predicted by the artificial neural network is given by neurons in the output layer. [11, 12]. For several decades, artificial neural network had been employed to several civil engineering problems like detecting structural damage, predicting results of experimental works, and mix proportions of concrete [13]. Yeh [14] showed that ANNs could able to easily forecast the compressive strength of high performance concrete from several mix proportions of concrete .Kasperkiewicz et al. [15] found that ARTMAP type neural network could be employed for predicting compressive strength in high performance concrete.

Table 1: Database used for neural network modeling,[3],[8].

Serial number	AS days	C (kg/m3)	MK (kg/m3)	SF (kg/m3)	W (kg/m3)	A (kg/m3)	S (kg/m3)	SP (kg/m3)	fc Exp
1	1	475	25	0	135	1050	720	43	35
2	1	475	0	25	135	1050	725	43	35
3	1	500	0	0	150	1050	695	19	48
4	1	425	75	0	150	1050	680	19	38
5	1	425	0	75	150	1050	680	19	38
6	1	450	50	0	165	1050	690	12	34
7	1	450	0	50	165	1050	685	12	32
8	3	475	25	0	135	1050	720	43	67
9	3	475	0	25	135	1050	725	43	63
10	3	500	0	0	150	1050	695	19	63.5
11	3	425	75	0	150	1050	680	19	60.5
12	3	425	0	75	150	1050	680	19	57.5
13	3	450	50	0	165	1050	690	12	59
14	3	450	0	50	165	1050	685	12	53
15	3	475	25	0	150	1087	721	0.6	73
16	3	475	0	25	150	1087	716	0.6	67
17	3	390	20.5	0	205	1081	659	0	32.6
18	3	390	0	20.5	205	1081	655	0	27.4
19	7	475	25	0	135	1050	720	43	76.5
20	7	475	0	25	135	1050	725	43	75.5
21	7	500	0	0	150	1050	695	19	72
22	7	425	75	0	150	1050	680	19	80
23	7	425	0	75	150	1050	680	19	74.5
24	7	450	50	0	165	1050	690	12	74
25	7	450	0	50	165	1050	685	12	70.5
26	7	475	25	0	150	1087	721	0.6	88.2
27	7	475	0	25	150	1087	716	0.6	79.3
28	7	390	20.5	0	205	1081	659	0	45.9
29	7	390	0	20.5	205	1081	655	0	47
30	28	475	25	0	135	1050	720	43	89
31	28	475	0	25	135	1050	725	43	88.5
32	28	500	0	0	150	1050	695	19	83.5
33	28	425	75	0	150	1050	680	19	94.5
34	28	425	0	75	150	1050	680	19	98.5
35	28	450	50	0	165	1050	690	12	84.5
36	28	450	0	50	165	1050	685	12	89.5
37	28	475	25	0	150	1087	721	0.6	103.6
38	28	475	0	25	150	1087	716	0.6	106.5

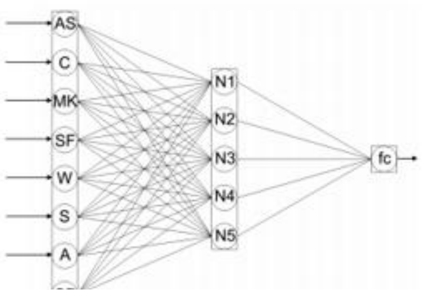
39	28	390	20.5	0	205	1081	659	0	57.1
40	28	390	0	20.5	205	1081	655	0	54.3
41	56	475	25	0	135	1050	720	43	95
42	56	475	0	25	135	1050	725	43	93
43	56	500	0	0	150	1050	695	19	84.5
44	56	425	75	0	150	1050	680	19	96.5
45	56	425	0	75	150	1050	680	19	101.5
46	56	450	50	0	165	1050	690	12	87
47	56	450	0	50	165	1050	685	12	90.5
48	90	475	25	0	135	1050	720	43	98
49	90	475	0	25	135	1050	725	43	96.5
50	90	500	0	0	150	1050	695	19	85.5
51	90	425	75	0	150	1050	680	19	97.5
52	90	425	0	75	150	1050	680	19	104
53	90	450	50	0	165	1050	690	12	89
54	90	450	0	50	165	1050	685	12	92
55	90	475	25	0	150	1087	721	0.6	112.9
56	90	475	0	25	150	1087	716	0.6	110.2
57	90	390	20.5	0	205	1081	659	0	66.5
58	90	390	0	20.5	205	1081	655	0	67.5
59	180	475	25	0	135	1050	720	43	99
60	180	475	0	25	135	1050	725	43	97.5
61	180	500	0	0	150	1050	695	19	87.5
62	180	425	75	0	150	1050	680	19	99.5
63	180	425	0	75	150	1050	680	19	106.5
64	180	450	50	0	165	1050	690	12	92.5
65	180	450	0	50	165	1050	685	12	93.5

Methodology

Currently this study uses a multilayered feed forward neural network, the data, matrix size of [65x9] were obtained from the literature [3][8],collected data is divided into three groups' viz., train data, validation data, and test data. The sequence of records was shuffled to have good diversity of records in training, testing and validation. At first, data in the records were normalized by considering individual data and dividing the same by the maximum value of the individual parameter. Thus make all the data lie between 0 and 1. This has been done to achieve faster training and avoid getting stuck in local optima. For ANN-(A) The matrix size test data [37x9] and train data is [14x9], while the matrix size of validation data is [8x9] .The various inputs are SF, W, S, A ,AS, C, SP ,and MK, For ANN-(B) ,32 records with AS, SP, SF, A, S, W, and C are taken as input and For ANN-(C) ,32 records with MK, A, S, W, AS, SP, and C are taken as input, while fc value was used as output for all the three models . Neural network model was developed using Neuroshell software package, back propagation algorithm was used .the logistic sigmoidal function at input layer, and linear function in the output layer. While hyperbolic tangent sigmoidal function was used in the hidden layer.

Table 2: values of parameters used in ANN-(A), ANN-(B), and ANN-(C)

parameter	ANN-A	ANN-B	ANN-C
No of input layer neurons	8	7	7
No of hidden layer	1	1	1
No of neurons in hidden layer	5	3	2
No of output layer neurons	1	1	1
Learning rate	0.1	0.1	0.1
Momentum rate	0.1	0.1	0.1
Learning cycle	100000	100000	100000



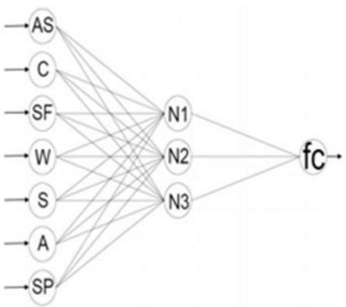


Fig.2 The system used in the ANN-(B) model

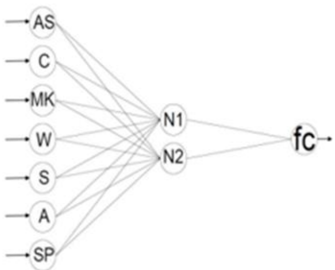


Fig.3. The system used in the ANN-(C) model

In ANN-(A) model, (Fig 1) ,5 neurons were clinched in the hidden layer as a result of its optimum R^2 values for testing and training sets. In ANN-(B) model, (Fig 2). 3 neurons were clinched in the hidden layer as a result of its optimum R^2 values for training and validation sets, In ANN-(C) model, (Fig 3). 2 neurons were clinched in the hidden layer as a result of its optimum R^2 values for training and validation sets. The neurons of all the three layers are linked through weights. At last, the predicted result is got through the output layer neurons. Values of momentum rate and learning factor were clinched for all the three models by several trials. The trained model was tested and the outcomes were established near to actual experimental outcomes.

Results and discussions

To look how near the predicted value is with the actual compressive strength, four indices, Coefficient of determination R^2, mean absolute error MAE, root mean square error RMSE, were employed to assess the conduct of ANN model. The result of training ,testing, validation phase in (Fig 4.1),(Fig 4.2),(Fig 4.3),(Fig 5.1),(Fig 5.2),(Fig5.3),(Fig 6.1),(Fig 6.2),(Fig 6.3) exhibit that the ANN-(A),ANN-(B) and ANN-(C) models are adequate enough to discern between input and output variables with sensibly good predictions. The statistical parameter values of co efficient of determination (R^2) clearly showed this position. For ANN-(A) the statistical values of R^2, MAE,

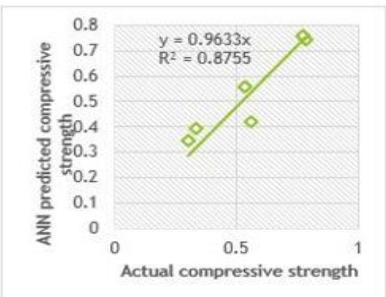


Fig 4.1 ANN-(A) performance with validation data

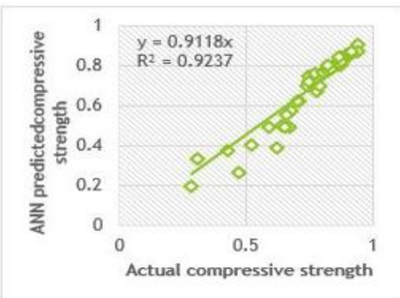


Fig 4.2 ANN-(A) performance with training data

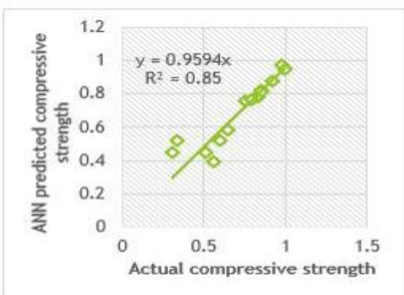


Fig 4.3 ANN-(A) performance with testing data

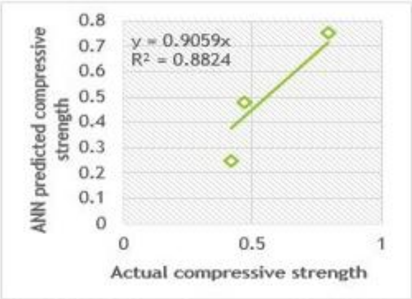


Fig 5.1 ANN-(B) performance with validation data

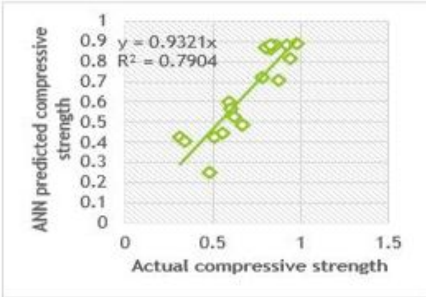


Fig.5.2 ANN-(B) performance with training data

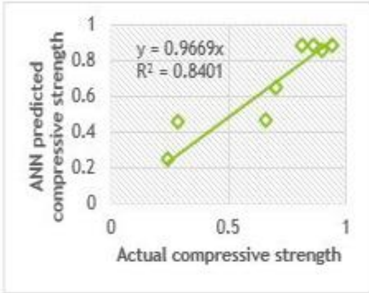


Fig 5.3 ANN-(B) performance with testing data

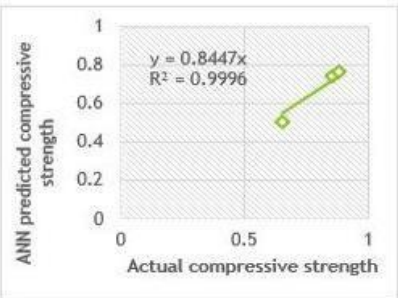


Fig 6.1 ANN-(C) performance with validation data

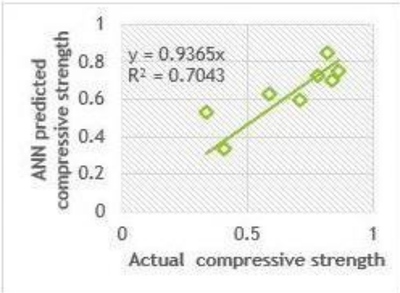


Fig 6.2 ANN-(C) performance with testing data

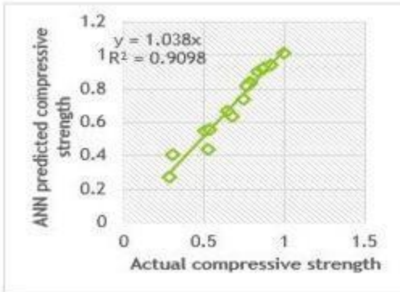


Fig 6.3 ANN-(C) performance with training data

RMSE was found as 0.9237, 0.073, and 0.089 respectively, these values were found in testing as 0.85, 0.066, and 0.083 respectively. Similarly, For ANN-(B) the statistical values of R^2, MAE, and RMSE from training found as 0.7904, 0.089, 0.1048 respectively, these values were found in testing as 0.8401, 0.078, and 0.1 respectively. For ANN-(C) the statistical values of R^2, MAE, RMSE from testing found as 0.7043,0.094 and 0.1095 respectively, R^2 value was found low due to insufficiency of data ,though the data shuffled several times. Statistical values of R^2, MAE, and RMSE from validation found as 0.9996, 0.128, and 0.1303, respectively. Obtaining R^2 values higher and closer to 1 and lower values of MSE and RMSE ensures good prediction. Hence, it is concluded that the performance of the neural network model is good.

Table 3: The statistical values of the proposed ANN-(A), ANN-(B) model, and ANN-(C) model.

Statistical parameters	ANN-(A)			ANN-(B)			ANN-(C)		
	Training set	Testing set	Validation set	Training set	Testing set	Validation set	Training set	Testing set	Validation set
R squared	0.9237	0.85	0.8755	0.7904	0.8401	0.8824	0.9098	0.7043	0.9996
Mean Absoluteerror	0.073	0.066	0.053	0.089	0.078	0.074	0.052	0.094	0.128
RMSE	0.089	0.083	0.070	0.1048	0.1	0.1	0.0707	0.1095	0.1303

Conclusion

This current study presents an new approach of compressive strength also shows the intelligence of the back propagation, multilayer feed forward neural network as a noble system for modelling the compressive strength of concrete The ANN model operate amply in assessing the compressive strength of concrete .The high R^2values clearly indicate that the neural network modeling is well suited The MSE values are fairly small implies that the outcomes are most accurate. Moreover, rendering to the compressive strength outcomes predicted by employing ANN-(A), ANN-(B) and ANN(C) models, the outcomes of ANN-(C) model are nearer to the actual investigation results. R^2, RMSE and MAE statistical values that are computed for matching experimental outcomes with ANN-(A) and ANN-(B) model results have shown this condition .This current study uses data set which contains limited data. Therefore, further study using more data sets is proposed which would bring out distinct conclusions. The conclusions have confirmed the prediction of compressive strength values of mortars comprising silica fumes and metakaolin using artificial neural networks.

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References

1. Gleize PJP, Cyr M, Escadeillas G. Effects of metakaolin on autogenous shrinkage of cement pastes. Cement Concrete Compos 2007;29(2):80–7.
2. Vu DD, Stroeven P, Bui VB. Strength and durability aspects of calcined kaolin-blended Portland cement mortar and concrete. Cement Concrete Compos 2001;23(6):471–8.
3. Poon CS, Kou SC, Lam L. Compressive strength, chloride diffusivity and pore structure of high performance metakaolin and silica fume concrete. Constr Build Mater 2006;20(10):858–65.
4. Parande AK, Babu BR, Karthik MA, Deepak Kumaar KK, Palaniswamy N. Study on strength and corrosion performance for steel embedded in metakaolin blended concrete/mortar. Constr Build Mater 2008;22(3):127–34.
5. Sabir BB, Wild S, Bai J. Metakaolin and calcined clays as pozzolans for concrete: a review. Cement Concrete Compos 2001;23(6):441–54.
6. Al-Amoudi OSB, Maslehuddin M, Shameem M, Ibrahim M. Shrinkage of plain and silica fume cement concrete under hot weather. Cement Concrete Compos 2007;29(9):690–9.
7. Curciol F, Deangelis BA. Dilatant behavior of superplasticized cement pastes containing metakaolin. Cement Concrete Res 1998;28(5):629–34.
8. Wong HS, Abdul Razak H. Efficiency of calcined kaolin and silica fume as cement replacement material for strength performance. Cement Concrete Res 2005;35(4):696–702.
9. Altun F, Kisi Ö, Aydin K. Predicting the compressive strength of steel fiber added lightweight concrete using neural network. Comput Mater Sci 2008;42(2):259–65.
10. Lippman R. An introduction to computing with neural nets. IEEE ASSP Mag 1987;4:4–22.
11. Mansour MY, Dicleli M, Lee JY, Zhang J. Predicting the shear strength of reinforced concrete beams using artificial neural network. Eng Struct 2004;26(6):781–99
12. Demir F. Prediction of elastic modulus of normal and high strength concrete by artificial neural network. Constr Build Mater 2008;22(7):1428–35
13. .Kewalramani AM, Gupta R. Concrete compressive strength prediction using ultrasonic pulse velocity through artificial neural networks. Auto Constr 2006;15(15):374–9
14. I.-C. Yeh, “Modeling of strength of high-performance concrete using artificial neural networks,” Cement and Concrete Research,1998; 28(12), 1797–1808.
15. J. Kasperkiewicz, A. Dubrawski, “HPC strength prediction using artificial neural network,” Journal of Computing in Civil Engineering, 1995;9 (4) 279–284.
16. artificial neural network training algorithms in predicting protozoa risks in surface waters,” Journal of Environmental Engineering, 2002;128 (6), 533-542.
17. K.P. Sudheer, K. Srinivasan, T.R. Neelakantan, V.V. Srinivas, “A nonlinear data-driven model for synthetic generation of annual streamflows,” Hydrological Processes,2008; 22 (12), 1831-1845.

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