International Journal of Science and Research (IJSR)
ISSN (Online): 2319-7064
Index Copernicus Value (2016): 79.57 | Impact Factor (2015): 6.391

Predicting Compressive Strength of Self-Compacting Concrete Using Bagasse Ash and Rice Husk Ash

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Abstract: ***Self-compacting concrete (SCC) is one of the types of concrete which will compact by its own weight. Now a day's, due to the increase in cost of cement and sand it is very much important to think for other materials as a replacement of concrete materials. This paper presents the comparative performance of the models developed to predict 28 to 180 days compressive strengths using neural network techniques for the data taken from experimentally for SCC mixes containing rice husk ash and baggase ash as partial replacement of cement and quarry dust in fine aggregates with two different topologies. The data used in the models are arranged in the format of nine input parameters and are cement, fine aggregate, coarse aggregate, water content, rice husk ash, baggase ash, quarry dust, water cement ratio and superplasticizer dosage and an output parameter is 28 to 180 days compressive strength of two different topologies 9-8-7 and 9-9-7. The significance of different input parameters is also given for predicting the strengths at various ages using neural network. The performance of the model can be judged by the normalized root-mean-square error, coefficient of correlation and average absolute relative error. The results of the present investigation indicate that artificial neural network have strong potential feasible tool for predicting compressive strength of concrete.***

Keywords: Artificial Neural Network, Concrete, Compressive Strength, Bagasse ash, Rice husk ash, Quarry dust

1. Introduction

Soft computing techniques are fuzzy logic, probabilistic reasoning, neural networks, and genetic algorithms. In recent years, Artificial Neural Network (ANN) has shown exceptional performance as regression tool, especially when used for pattern recognition and function estimation. They can capture highly non-linear and complex relations among input/output variables in a system without any prior knowledge about the nature of these interactions. ANNs are very efficient in predicting the concrete degree of hydration with great accuracy by using minimal processing data that applied a neural network model for performed foam cellular concrete. Results showed that the production yield, foamed and un-foamed density, compressive strength of cellular concrete mixes can be predicted much more accurately using the ANN method compared to existing parametric methods [1]. In the world, concrete is one of the most widely used construction material, concrete has been fabricated from a few well-defined components viz: cement, water, fine and coarse aggregates, etc. In the concrete mix design and quality control, the strength of concrete is a very important property. Predicted properties of cement paste are of great significance and difficult to achieve as a function of the mixture gradient and physical properties of concrete. So, nonlinear prediction models are considered. The uncertainties are associated with the parameters affecting the density and compressive strength of cement paste which makes it difficult to exactly estimate such properties of concrete [2]. Prediction of cement degree of hydration using ANN is very efficient with the great accuracy using minimal processing data [3]. ANN model for performed foam cellular concrete, results showed that the production yield, foamed density, unfoamed density and the compressive strength of cellular concrete mixtures can be predicted much more accurately using the ANN method compared to existing parametric methods [4]. The predicted performances of SCC for different mixes are used [5].

Recent days self compacting concrete (SCC) as new type of concrete, which flows under its own weight without need for any external compaction or vibration. SCC was first introduced in the late 1980's by Japanese researchers, as highly workable concrete that can flow under its own weight through restricted sections without segregation and bleeding. [6].This saves the time, reduces overall cost, improves the quality of concrete, improves working environment and reduces the labours works [8]. In the production of SCC, several different approaches can be used. In one method to achieve self-compacting property is to increase significantly the amount of fine materials. Workability of SCC depends on a number of interrelating factors such as water cement ratio, aggregate to cement ratio, types of superplasticizers and its dosage, aggregate type and its grading. Due to its excellent workability, mechanical property and durability, SCC is extensively used in concreting projects. SCC has become an important research and application aspect of the high-performance concrete. In recent years, a number of research and application on self-compacting concrete have been carried out [9]. Compressive strength is the most important mechanical property of concrete, it is primarily used as quality control, in addition to its other important properties of concrete, including flexural strength, splitting tensile strength, and modulus of elasticity, which are directly related to compressive strength [10]. The several techniques based on either empirical methods or computational modelings have been tested, and empirical methods based on multi-linear regression is commonly proposed to predict compressive strength [11].

2. Artificial Neural Networks

Artificial Neural Network (ANN) is a computational model that tries to simulate the structure and functions of biological neural networks of the central nervous system. Information that flows through the network affects the structure of the ANN because it is a neural network. ANN can be trained to solve certain problems in any different fields. In this way, identically constructed ANN can be used to the perform different tasks depending on the training received. Artificial Neural Networks are the powerful tool for the purpose of prediction and recognition of patterns. ANNs can also well suited for problem whose solutions require knowledge that is difficult to specify but for which there are enough data [12]. In addition to the processing elements called "neurons", the neural networks comprise of the connections between the processing elements. The connections carry a weight. Weight coefficients are the key elements of every neural network. Weights are the connections between different layers that have much significance in working of the neural networks and the characterizing of a network. Start the network with one set of weight and run the network once, modify some or all the weights and run the network again and repeat the process until some predetermined goal is met. The back-propagation provides a computationally efficient method for changing the weights in a feed forward network, with differentiable activation units to learn a training set of input-output examples [13]. ANN methodology has been used for modeling a variety of problems and phenomenon encountered in the field of Civil Engineering problems.

This present study is an effort to apply neural network-based system identification of techniques to predict the compressive strength of concrete based on the concrete mix proportions. For this study a computer program is developed using artificial neural network design toolbox in MATLAB from the Math Works [14]. Using this program, a neural network model with different hidden layers is constructed, trained, and tested using the available test data sets. The data used in ANN model are arranged in a format of nine input parameters that covers the cement content, fine aggregate content, coarse aggregate content, water cement ratio, rice husk ash, bagasse ash, superplastizer, quarry dust and water. The proposed ANN model predicts the 28th to 180th day's compressive strength of concrete. The main objective of this study is to develop a neural network based model for predicting compressive strength of concrete of SCC mixes, with the experimentally obtained data.

3. Materials and Methods

Cement is the fine material which is used as a binding material. Ordinary Portland cement 43 grade was used. It is confirming to the requirement of Indian standard specification IS: 8112-1989 [15]. The physical properties are given in Table 1. The tests on cement have been carried out as IS: 4031- 1999. The sieve analysis of fine aggregate has been carried out as per IS 383-1970[17] and from that it is confirmed to grading zone-II and other properties of fine aggregate are shown in Table 2. The common coarse aggregates used are crushed stone and gravel. The 16 mm downsize coarse aggregate was tested as per IS 2386 (I, II, III) specifications and the properties are given in Table 2. It is confirming to the requirement of Indian standard specification IS: 383-1970 [17]. Quarry dust comprises the smaller aggregate particles, so it was sieved and quarry dust passing from 4.75mm IS sieve and retaining on 150 micron IS sieve is used for the replacement of fine aggregate. The sieve analysis of fine aggregate has been carried out as per IS 383-1970 [17] and from that it is confirmed to grading zone-II and other properties of fine aggregate are shown in Table 2. The rice husk ash had greyish white colour. RHA passed through IS 90 micron sieve was used. The specific gravity at 27^{o}C is 2.18 and bulk density is 895 kg/m^3 determined as per IS 1727-1967 [16]. The bagasse ash is collected sugar factory was used in this study**.** The ash obtained in the factory was coarser and it was put to the ball mill to convert them into fine particles of size most likely to the cement particles. Bagasse ash has grayish white color. Bagasse ash was passed through IS 90 micron sieve and this was used for the research. The specific gravity is 2.32 and bulk density is 1075 kg/m^3 determined as per IS 1727-1967 [16]. Admixtures mainly affect the flow behavior of the Self-compacting concrete. The admixture used here is Sika viscocrete 5231. The properties of this admixture are Relative density at 25^{0}C is 1.08, pH is 7.25 and bluish brown colour.

Table 1: Properties of Ordinary Portland cement

S. No.	Physical test		Results obtained	Requirement IS: 8112-1989
1	Fineness (%)		5.50	10 maximum
2	Specific gravity		3.05	-
3	Vicat time of setting (minutes)	Initial setting time	80	30 minimum
		Final setting time	325	600 maximum
4	Compressive Strength (MPa)	3 day	24.00	23.00 minimum
		7 day	35.00	33.00minimum
		28 day	45.20	43.00 minimum

Table 2: Physical Properties of Fine Aggregate, Quarry Dust and Coarse Aggregate

Property		Materials		
		Fine Aggregate	Quarry Dust	Coarse Aggregate
Bulk density Kg/m^3	Loose state	1552.00	1520.00	1465.00
	Rodded state	1645.00	1615.00	1595.00
Specific gravity		2.55	2.45	2.62
Fineness modulus		2.97	2.88	6.90
Surface Moisture (%)		1.45	2.35	Nil
Water absorption (%)		1.53	2.80	0.15

4. Mix proportions, Preparation and Casting of Test Specimens

Several trial mixes are prepared by changing the volume ratio of fine aggregate, coarse aggregate, water/powder ratio and super plasticizer. On the basis of the test results many trail mixes are conducted in the laboratory and final mix proportion which satisfies the fresh concrete properties as per EFNARC 2002 [7] guidelines is selected for control concrete mix. The final mix proportion is the reference mix of SCC mixes with different replacement level of bagasse ash, RHA and QD. For all the mixes coarse aggregate content is kept constant and are given in Table 3. These mixes are tested as per EFNARC [7] and satisfied their requirements. Aall the specimens were then cured in water until the specified date of testing [7]. The fresh concrete properties such as filling ability and passing ability (Slump flow test, SlumpflowT$_{50\ cm}$, J-ring test, V-funnel test, V-funnel 5 minitues and L box) were carried out according to EFNARC [7]. Hardened concrete properties such as compressive strength were carried out according to IS specification [18].

Table 3: Mix proportion for SCC mixes

Mix Notation	Cement (kg/m^3)	BA (kg/m^3)	RHA (kg/m^3)	FA (kg/m^3)	QD (kg/m^3)	CA (kg/m^3)	W/c ratio	SP (%)
MBR1	450	0	0.00	891.00	0.00	742.50	0.46	0.50
MBR2	405	22.50	22.5	712.00	179.00	742.50	0.46	0.50
MBR3	405	22.50	22.50	623.70	267.30	742.50	0.48	0.50
MBR4	405	22.50	22.50	534.60	356.40	742.50	0.48	0.50
MBR5	405	22.50	22.50	445.50	445.50	742.50	0.50	0.60
MBR6	405	22.5	22.5	267.30	623.70	742.50	0.55	0.60
MBR7	360	45.00	45.00	712.00	179.00	742.50	0.50	0.50
MBR8	360	45.00	45.00	623.70	267.30	742.50	0.52	0.55
MBR9	360	45.00	45.00	534.60	356.40	742.50	0.52	0.50
MBR10	360	45.00	45.00	445.50	445.50	742.50	0.55	0.60
MBR11	360	45.00	45.00	267.30	623.70	742.50	0.55	0.60
MBR12	315	67.50	67.50	712.00	179.00	742.50	0.52	0.50
MBR13	315	67.50	67.50	623.70	267.30	742.50	0.53	0.65
MBR14	315	67.50	67.50	534.60	356.40	742.50	0.55	0.50
MBR15	315	67.50	67.50	445.50	445.50	742.50	0.55	0.70
MBR16	315	67.50	67.50	267.30	623.70	742.50	0.55	0.65

5. Training of ANN Model

In this study, multilayered feed forward neural network with a back propagation algorithm was adopted. The possible training parameters are number of iterations (epoch) learning rate, error goal and number of hidden layers. These parameters are varied until a good convergence of ANN training is obtained and there by fixing the optimal training parameters. The numbers of neurons in the input layer and output layer are determined based on the problem domain depending upon number of input variables and number of output or target variables. The number of hidden layers and neurons in hidden layer are fixed during the training process. Two different topologies 9-8-7 and 9-9-7 ANN architectures were built. The training and testing of the ANN models constituted with two different topologies. The basic parameters are considered in present study were cement, coarse aggregate, fine aggregate, quarry dust, water, bagasse ash, rice husk ash, superplastizer and w/c ratio and they were entered as input, while compressive strength value was used as output, in the topology of model 9-8-7 and 9-9-7. The data were randomly divided into a training phase. In the present study 80% data generated was used for training and the remaining 20% data was used for testing the network. For the topology of model 9-8-7 and 9-9-7, the neurons of neighboring layers are fully interconnected by weights. Finally, the output layer neuron produces the network prediction as a result. Momentum rate and learning rate values were determined for both the topology models which were trained through iterations. The values of parameters used in topology of model 9-8-7 and 9-9-7 are given in Table 4 and are used to predict the compressive strength. The trained models were only tested with the input values and the results found were close to experiment results.

Table 4 Parameter use to develop ANN architectures

Network parameter	Topology of model 9-8-7	Topology Model 9-9-7
Number of inputs	9	9
Number of network output	7	7
Network training function	Levenberg-Marquardt	Levenberg-Marquardt
Network performance function	Mean square error	Mean square error
Number of Hidden Layer	1	1
Number of hidden layer neurons	9	8
Validation checks	6	6
Learning Rate	0.50	0.50
Iteration	217	106

6. Results and Discussion

Table 5: Details of Compressive Strength of SCC Mixes

Mix Notation	Experimental Compressive Strength (MPa)						
	7 Day	14 Day	28 Day	56 Day	91 Day	120 Day	180 Day
MBR1	28.17	29.55	42.17	45.96	47.78	48.09	50.09
MBR2	27.11	29.78	36.95	42.73	44.04	45.02	47.13
MBR3	27.15	28.51	32.83	35.11	39.07	41.00	42.32
MBR4	26.58	32.01	37.17	42.85	43.02	44.07	45.95
MBR5	27.86	33.28	40.92	43.45	45.86	47.00	48.47
MBR6	27.15	31.10	38.98	41.00	41.68	43.22	44.30
MBR7	22.02	28.92	35.2	37.23	38.09	40.27	41.23
MBR8	19.42	22.82	26.52	28.91	33.89	34.58	38.11
MBR9	21.84	22.65	25.17	28.56	33.20	34.42	37.76
MBR10	19.40	22.01	25.93	29.12	32.87	33.21	35.68
MBR11	18.80	20.27	24.93	28.71	30.29	32.67	35.42
MBR12	17.26	19.02	25.60	27.30	28.93	31.30	32.93
MBR13	16.38	18.71	23.20	24.53	26.56	29.82	31.86
MBR14	16.08	18.00	21.93	23.29	24.67	25.69	27.82
MBR15	14.33	15.93	18.95	20.70	22.00	22.98	24.57
MBR16	12.35	14.78	17.26	20.22	22.41	22.73	24.30

Table 6: Statistical performance for the Models for Compressive Strength of SCC Mixes

Parameter	Topology of the ANN Model			
	9-8-7		9-9-7	
	Training	Testing	Training	Testing
CC	0.9997	0.9997	0.9999	0.9999
NRMSE	0.006325195	0.082551439	0.003057932	0.077771723
AARE (%)	0.491440318	6.790348633	0.253777136	6.23400169

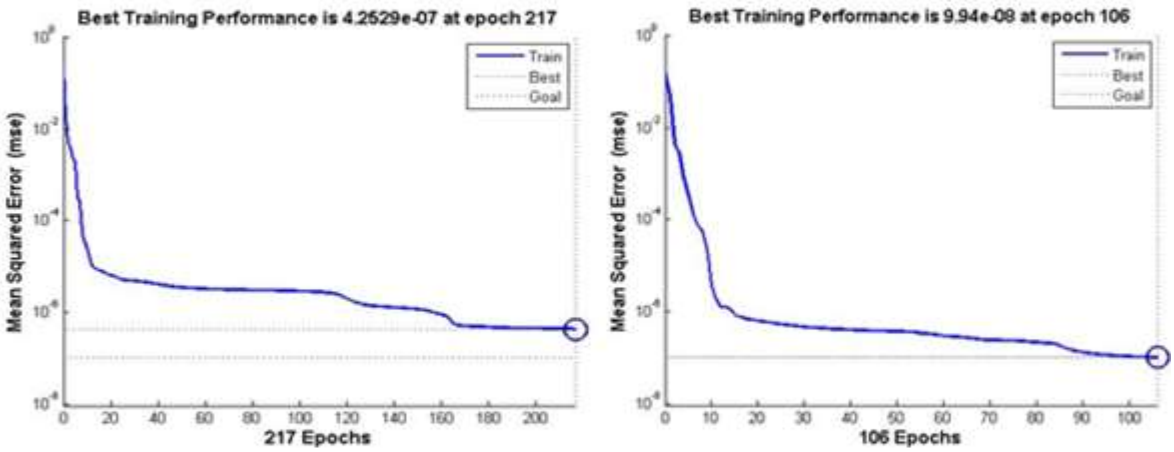

Figure 1: Training Curves for Prediction of Compressive Strength of SCC Mixes

Table 7: Predicted Training and Testing Outputs of the Compressive Strength of SCC Mixes

Mix Notation	7 Day	14 Day	28 Day	56 Day	91 Day	120 Day	180 Day
Topology of the ANN Model 9-8-7							
Training Output							
MBR1	28.16	29.58	42.13	45.99	47.80	48.03	50.08
MBR2	27.15	29.53	37.20	42.47	43.83	45.39	47.15
MBR3	27.08	28.73	32.62	35.33	39.18	40.66	42.36
MBR5	27.92	33.28	40.81	43.52	46.05	46.91	48.31
MBR6	27.12	31.11	38.99	40.97	41.60	43.25	44.36
MBR7	22.00	28.90	35.23	37.20	38.03	40.28	41.28
MBR8	19.52	22.75	26.46	28.86	33.98	34.75	37.94
MBR10	19.18	21.80	26.43	28.87	32.37	33.37	36.07
MBR11	18.85	20.28	24.85	28.75	30.41	32.61	35.32
MBR12	17.15	19.54	25.08	27.77	29.26	30.65	32.90
MBR14	16.33	17.83	22.00	23.01	24.62	26.03	27.72
MBR15	14.18	15.75	19.13	20.70	21.97	23.10	24.51
MBR16	12.41	14.85	17.18	20.22	22.41	22.68	24.31
Testing output							
MBR4	27.66	31.73	39.54	44.53	44.54	46.61	47.60
MBR9	19.72	22.74	27.30	30.88	35.82	36.45	40.02
MBR13	15.58	17.95	22.82	22.94	22.88	24.69	25.52
Topology of the ANN Model 9-9-7							
Training Output							
MBR1	28.18	29.54	42.16	45.97	47.74	48.11	50.09
MBR2	27.09	29.78	36.95	42.69	44.06	45.00	47.12
MBR3	27.16	28.51	32.81	35.10	39.10	40.96	42.31
MBR5	27.90	33.33	40.86	43.44	46.01	46.85	48.45
MBR6	27.16	31.01	38.98	41.07	41.47	43.37	44.31
MBR7	21.98	28.94	35.22	37.16	38.13	40.24	41.23
MBR8	19.49	22.73	26.45	29.04	33.75	34.65	38.10
MBR10	19.25	22.03	26.08	28.97	32.76	33.34	35.71
MBR11	18.77	20.35	24.93	28.63	30.46	32.54	35.41
MBR12	17.25	19.04	25.59	27.26	29.03	31.22	32.92
MBR14	16.12	17.93	21.92	23.381	24.40	25.85	27.83
MBR15	14.26	16.03	18.95	20.55	22.35	22.72	24.54
MBR16	12.47	14.69	17.17	20.37	22.24	22.81	24.29
Testing Output							
MBR4	30.44	32.97	39.21	40.34	42.70	44.90	46.11
MBR9	20.68	21.60	25.17	26.17	30.75	32.24	36.99
MBR13	14.29	19.36	23.74	26.06	25.33	25.69	24.94

Table 8: Percentage Error between Actual and Predicted Compressive Strength of SCC mixes

Mix Notation	7 Day	14 Day	28 Day	56 Day	91 Day	120 Day	180 Day
Topology of the ANN Model 9-8-7							
Training Output							
MBR1	0.01	0.11	0.07	0.06	0.05	0.10	0.00
MBR2	0.16	0.83	0.69	0.58	0.46	0.84	0.04
MBR3	0.24	0.799	0.63	0.64	0.29	0.81	0.09
MBR5	0.22	0.029	0.25	0.18	0.42	0.18	0.32
MBR6	0.08	0.04	0.05	0.06	0.18	0.08	0.14
MBR7	0.06	0.06	0.10	0.06	0.14	0.04	0.12
MBR8	0.53	0.29	0.21	0.17	0.27	0.51	0.44
MBR10	1.10	0.92	1.95	0.84	1.51	0.49	1.09
MBR11	0.26	0.05	0.30	0.17	0.42	0.17	0.26
MBR12	0.61	2.78	2.02	1.73	1.17	2.06	0.08
MBR14	1.57	1.03	0.35	1.19	0.19	1.33	0.33
MBR15	1.01	1.10	0.96	0.00	0.09	0.52	0.20
MBR16	0.49	0.47	0.45	0.00	0.03	0.20	0.07
Testing output							
MBR4	4.09	0.84	6.38	3.94	3.55	5.76	3.60
MBR9	9.68	0.43	8.47	8.15	7.89	5.91	5.99
MBR13	4.87	4.02	1.60	6.47	13.82	17.17	19.87
Topology of the ANN Model 9-9-7							
Training Output							
MBR1	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MBR2	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MBR3	0.00	0.00	0.00	0.00	0.00	0.00	0.00
MBR5	0.16	0.15	0.13	0.00	0.33	0.30	0.03
MBR6	0.03	0.27	0.01	0.17	0.48	0.35	0.02
MBR7	0.17	0.07	0.06	0.16	0.11	0.06	0.00
MBR8	0.37	0.38	0.22	0.47	0.40	0.23	0.00
MBR10	0.75	0.09	0.60	0.49	0.32	0.41	0.08
MBR11	0.13	0.37	0.01	0.27	0.57	0.37	0.02
MBR12	0.04	0.13	0.03	0.13	0.36	0.24	0.02
MBR14	0.27	0.34	0.03	0.39	1.06	0.65	0.04
MBR15	0.44	0.66	0.02	0.71	1.62	1.09	0.08
MBR16	1.01	0.57	0.48	0.76	0.72	0.36	0.00
Testing output							
MBR4	14.52	3.02	5.50	5.85	0.74	1.89	0.36
MBR9	5.26	4.60	0.03	8.33	7.37	6.32	2.03
MBR13	12.70	3.52	2.356	6.27	4.62	13.84	21.00

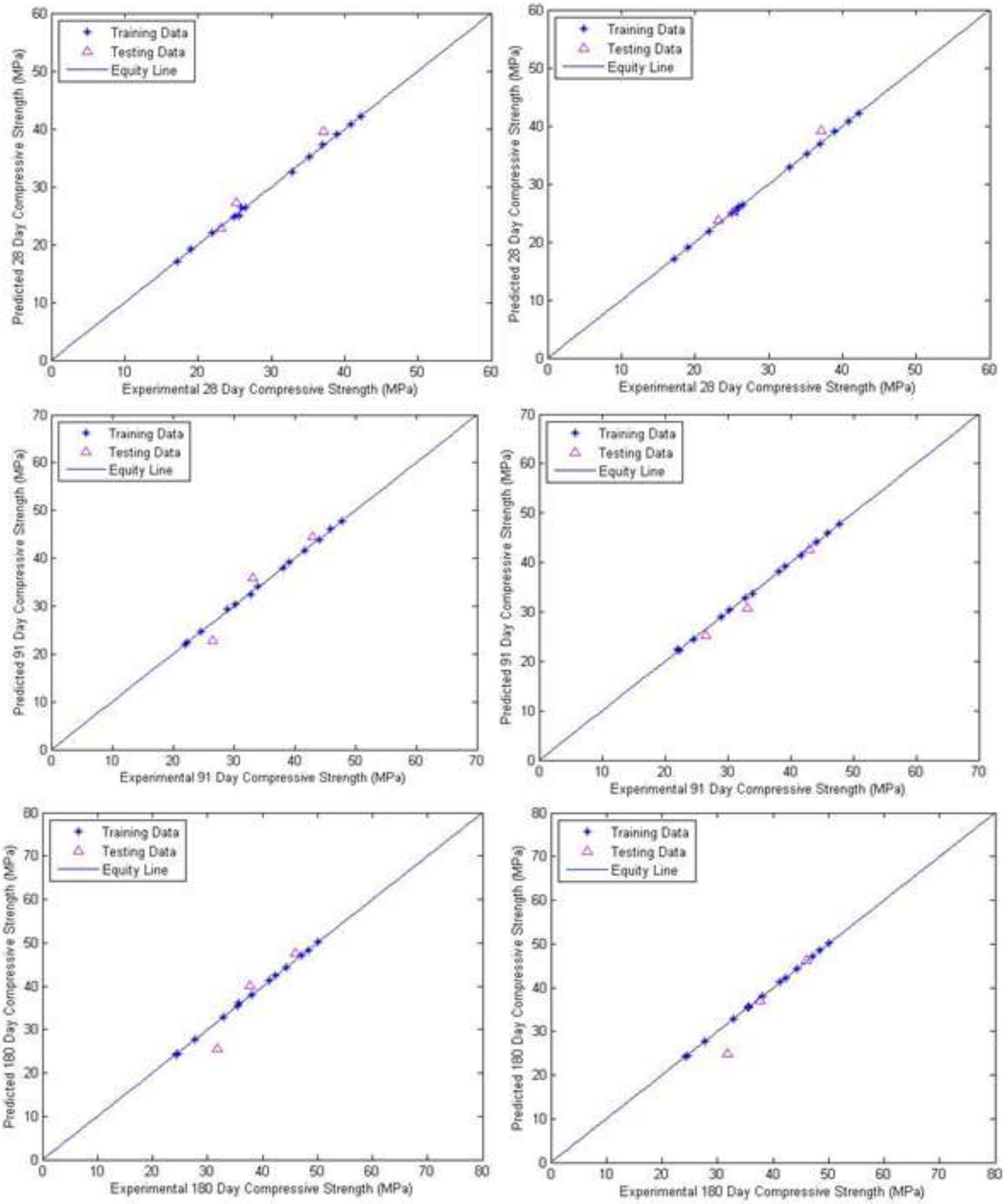

Figure 2: Comparison of the experimental and predicted compressive strength with training and testing results of 28, 91 and 180 days for Topologies 9-8-7 and 9-9-7

The results of compressive strength of cubes for 28 to 180 days curing are given in Table 5. The optimum dataset of the representative concrete mix proportion is used for developing the ANN model to predict the compressive strength of concrete. ANN models with two topologies are used. During experiments, it is found that the LM back propagation is the best possible training function with correlation equal to or greater than 95% on an average. The results of predicted compressive strength of each simulation data are given in Table 7. The predictions of the best ANN model are graphically shown in Fig. 1. The statistical values such as normalized root-mean-square error (NRMSE), coefficient of correlation (CC), average absolute relative error (AARE) are given in Table 6 and are used to judge the performance of the neural network approach in predicting the strength. It is found that the values obtained from the training and testing in topology of model 9-8-7 and 9-9-7, were very closer to the experimental results.

Fig. 1 shows the mean square error convergence history. The mean square error with regularization for the best validation performance occurred at 4.2529e-07 for 217 epoch. In Fig. 1, the gradient at 217 epochs is 0.0609. The mean square error with regularization for the best validation performance occurred at 9.94e-08 for 106 epoch. In Fig. 1, the gradient at 106 epochs is 0.0602. The visualization of the training graph shows smooth convergent appears for both topology 9-8-7 and 9-9-7 as shown in Fig. 1.

From the Table 8, it is observed from the results of ANN with topology 9-8-7 in training and testing modes, the difference between the predicted and experimental compressive strength are varies in the range of 0.00 to 14.50 % for 7day, 0.00 to 4.60 % for 14 day, 0.00 to 5.50 % for 28 day, 0.00 to 5.85 % for 56 day, 0.00 to 7.37 % for 91 day, 0.00 to 13.84 % for 120 day, 0.00 to 21.69 for 180 day respectively. Similarly for the topology 9-9-7 in training and testing modes, the difference between the predicted and experimental compressive strength are varies in the range of 0.00 to 9.68 % for 7day, 0.00 to 4.02 % for 14 day, 0.0 to 8.47 % for 28 day, 0.00 to 8.15% for 56 day, 0.0 to 13.82 % for 91 day, 0.00 to 17.17% for 120 day, 0.00 to 19.87 % for 180 day respectively. The prediction compressive strength of SCC mixes is determined from experimental data. Fig. 2 shows the linear relationship between predicted and actual values for the model for both topologies 9-8-7 and 9-9-7, the linear relationship shows that there is correlation between actual and predicted values.

7. Conclusion

1) An empirically investigated the different architectural parameters such as the number of hidden neurons, learning rate, performance goal, epochs for the fine tuning of neural network of the model.
2) ANN model has been proposed to predict the compressive strength of concrete with the development of different topology of model.
3) The visualization of the training graph shows smooth convergent which appears for both topology 9-8-7 and 9-9-7.
4) The average predicted / experimental compressive strength values are more closed.
5) Both the topologies of models developed predicted compressive strength at various ages and the results in the form of correlation coefficient, normalized root-mean-square error and average absolute relative error were found to be better for both models.
6) Bagasse ash and rice husk ash is a by-product material, it is used as a cement replacing material which reduces the levels of CO_2 emission by the cement industry. In addition its use resolves the disposal problems associated with it in the sugar industries and thus keeping the environment free from pollution.

References

[1] Nehdi, M., jebbar, Y.D. and Khan, A. \Neural network model for cellular concrete", ACI Materials Journal, 98(5), pp. 402-409 (Sep.-Oct. 2001).
[2] Neville, A.M., Properties of Concrete, Longman Scientific & Technical (1995).
[3] Adnan, A., Basma, S.A. and Al-Orami, B.S. "Prediction of cement degree of hydration using artificial neural network", ACI Materials Journal, 96(2), pp. 167-172.
[4] Nehdi, M., jebbar, Y.D. and Khan, A. "Neural network model for cellular concrete", ACI Materials Journal, 2001, 98(5), pp. 402-409 (Sep.-Oct. 2001).
[5] Nehdi, M., Chabib, H.El. and Naggar, M.H.El. "Predicting performance of self-compacting concrete mixtures using artificial neural networks", ACI Materials Journal, 98(5), pp. 394-401 (Sept.-Oct. 2001).
[6] Okamura, H. Self-compacting high-performance concrete, Concrete international, 19 (7), 1997, pp.50-54.
[7] EFNARC-2002, "achieving and highest standards", Specification and Guidelines for Self-Compacted Concrete. EFNARC, Association house, 99 West Street, Farnham, Surrey GU9 7EN, UK.
[8] F.M. Almeida Filho, B.E. Barragan, J.R. Casas, A.L.H.C. El Debs, "Hardened properties of self-compacting concrete - A statistical approach", Construction and Building Materials, 24(9): 1608–1615, 2010.
[9] V. K. Bui and D. Montgomery I. Hinczak and K. Turner, "Rapid Testing Method for Segregation Resistance of Self-Compacting Concrete", Cement and Concrete Research, vol. 32, pp. 1489-96, September 2002.
[10] C. Deepa, K. Sathiyakumari, and V. Sudha, "Prediction of the compressive strength of high performance concrete mix using tree based modeling," International Journal of Computer Application, vol. 6, no. 5, pp. 18-24, September 2010.
[11] J. Noorzaei, S. J. S. Hakim, M. S. Jaafar, and W. A. M. Thanoon, "Development of artificial neural networks for predicting concrete compressive strength," International Journal of Engineering and Technology, vol. 4, no. 2, pp. 141-153, 2007.
[12] Zhang, B.E. Patuwo and M.Y. Hu, (1998), Forecasting with Artificial Neural Networks The State of the Art, International Journal of Forecasting, 14, 35-62.
[13] S.N. Shivanandam, S. Sumathi and S.N Deepa, (2012), Feed Forward Networks, in Introduction to Neural Networks using Matlab 6.0, 16th Reprint, Tata McGraw-Hill, India.
[14] The math works, MATLAB & Simulink , R2013a.
[15] IS: 8112-1982, Specification for 43-Grade Portland cement, Bureau of Indian Standards, New Delhi, India.
[16] IS: 1727: 1967, Indian Standard Methods of Tests for pozzolanic materials, Bureau of Indian Standards, New Delhi, India.
[17] IS: 383-1970, Specification for coarse and fine aggregate from material sources for concrete (Second Revision), Bureau of Indian Standards, New Delhi, India.
[18] IS: 516: 1959, Indian Standard code for practice, Methods of Tests for strength of concrete Bureau of Indian Standards, New Delhi, India.