Prediction of Strength of Hybrid Fibre Reinforced Self Compacting Concrete Using Artificial Neural Network

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Abstract. A Hybrid Fiber-Reinforced Self-Compacting Concrete (HFRSCC) is a new type of building material that combines the benefits of SCC with the additional benefit of fibres. The brittle SCC was transformed into a ductile material with the ideal amount of fibres; as a result, it flows into the formwork's interior with ease, passes through barriers, and compacts under its own weight. The Artificial Neural Network (ANN) has garnered increasing attention in the last several decades due to its capacity to handle multivariate analysis. As a result, the ANN model was created to ascertain the FRSCC's mechanical characteristics. A new JO-m Sigmoid ANN is employed for predicting the mechanical characteristics of SCC concrete that is 80 MPa and 60 MPa with the adding of 0.75 and 0.75 percent hybrid steel fibre. Using experimental data and four distinct datasets (datasets-1, 2, 3, and 4) the suggested model was verified. Regarding the different datasets, the suggested model demonstrated enhanced prediction ability in the range of 0.01% to 15.56%.

Keywords: FRC, SCC, Hybrid concrete, Strength properties, Prediction, ANN

1 Introduction

Concrete that self-compacts which is known as self compacting concrete (SCC) has a poor strain capacity and is brittle. Due to its propensity for cracks to appear during loading, SCC has poor tensile behaviour. Additionally, the fractures expand and eventually break, which alters the concrete's ductility behaviour. [1-2] By adding metal fibres to the concrete mix, this drawback of concrete may be addressed. Fiber-reinforced concrete (FRC) is the name given to this kind of concrete. The qualities of concrete will only be slightly enhanced by adding a single kind of fibre as a secondary reinforcement. [3-4] Hybrid fibres were employed to overcome this restriction and increase the concrete's qualities even more. According to the study, adding hybrid

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fibre to concrete may increase its strengths of split tensile, flexural , and compressive by 25%, 94%, and 175%, respectively, compared to adding single fibre.

A hybrid fibre is made up of two or more distinct fibre types that have been logically mixed to produce the intended outcomes. Fibre hybridization has the ability to stop cracking, improve extensibility and tensile strength, and support the matrix's ability to remain intact even after significant breaking. Hybrid fiber-reinforced concrete is defined as concrete that has had two or more types of fibre incorporated into it as a supplementary reinforcement in SCC. [5-6]

A computer model known as an artificial neural network (ANN) was developed based on the design and operation of biological neural networks such as those found in the human brain. It is a subset of algorithms used in machine learning (ML) that are intended to identify patterns, gain knowledge from data, and make judgments or predictions. Neural networks have several benefits over more conventional digital computing techniques, such as the capacity to learn from examples, generalize answers to new issue interpretations, be error-tolerant while processing data, and process data quickly.[7–12] Because ANNs may operate as universal function approximates, they are typically employed to represent issues where the relationship is not evident between the variables.

Neural networks are black boxes, thus no functional link between the various variables that has to be assumed. The ANN will automatically establish associations and adjust itself based on the training dataset. The capacity of ANN modeling to draw inferences from uncertain and non-linear interrelationships among variables has proven beneficial for engineering and natural system behaviour predictions. [13–14]

Objective of the research work: To ascertain the mechanical characteristics and of HFRSCC, using an ANN prediction model.

2 Methodology

DEVELOPMENT OF ANN

ANN, a computer method inspired by biological neural networks, is used to simulate the complicated non-linear connection. The construction of the model involves the use of a learning algorithm and a variety of ANN types. The back propagation multilayer perceptron (BPMLP) is a popular and extensively utilised approach for network training. This technique is based on the gradient descent approach, which modifies the weight in little steps to lower the error for a given training sequence. Applications in civil engineering frequently employ this methodology.

The organisation of neurons or nodes in a BPMLP is divided into three layers: input, output, and hidden. Each neuron linked with the weights is sent via the summation and activation function, which provides information to the neurons in the appropriate layer to produce the output. The individual layer neurons employ the same activation function to turn input signals into the desired output. The network architecture refers to the arrangement of neurons in a layer and their connections to other neurons and layers. The number of layers, neurons, activation function, and connections between each layer are all specified by the architecture of the network. Each layer's neurons are linked to the layer below's neurons. The training and reproduction stages are the two main phases of a neural network (NN). Each neuron's weight value indicates the degree to which an input influences it. There is no set rule for selecting the optimal number of nodes in the hidden layer, thus it is determined by experimentation.

The activation function determines the value of each neuron's output, and for all neurons with full attachment, the weighted input is mapped to each neuron's output using a non-linear activation function. When the network weights are changed in response to a predetermined mistake, the iterative training process comes to an end. During the model's training, the learning rate, momentum, stopping time, are important parameters in order to enhance the pace of convergence and prevent over fitting.

With the mixing of hybrid steel fibres, and micro-steel fibres in proportions of 0.5% and 0.75%, to the 60 and 80 MPa SCC, a developed JO-mSigmoid-ANN model is used to predict the flow and mechanical properties. The model takes into account input parameters like the amount of cement, fly ash, GGBS, micro-silica, M-sand, coarse aggregate, water, super-plasticizer, and micro and steel fibres provided at the input layer of JO-m Sigmoid-ANN. Figure 1 depicts the JO-m Sigmoid-ANN prediction model's design.

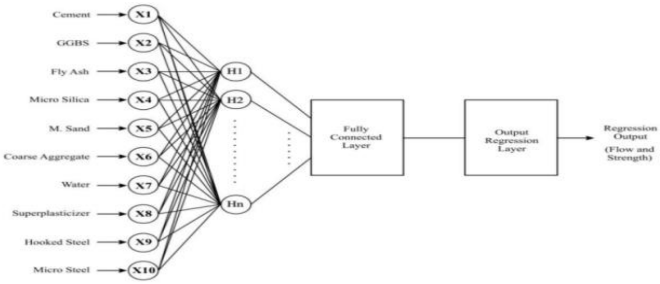

Fig.1 The architecture of the JO-m Sigmoid-ANN prediction model

3 Experimental Work

In this study, hybrid steel fibers—that is, hooked-end and micro steel fibres with varying volume percentage values of 0.5–0.75% in around ten distinct combinations—were added to SCC concrete of two different strengths, 60 MPa and 80 MPa. Experiments were performed to estimate the concrete's compressive, split tensile, flexural, elastic modulus, impact, and moment curvature relationship tests for reinforced concrete beams. Next, using regression analysis, a new jellyfish optimiser based modified sigmoid-activated artificial neural network model (JO-m Sigmoid-ANN) was created to forecast the flow and strength characteristics of the created SCC specimen.

PREPARATION OF HYBRID FIBRE REINFORCED SELF COMPACTING CEMENT CONCRETE:

High strength, and high durability are characteristics of HPSCC concrete, which is designed to last for a specific amount of time under specific loading and exposure circumstances. For the present work HPSCC was prepared using Cement, GGBS, fly ash, micro-silica, M-sand, coarse aggregate, super-plasticizers, fibres, and water. The mix quantities were shown in Tables 1 &2 below.

Table 1. Mix proportions used in this study (Part-1)

Mix ID	Cement	GGBS	Flyash	Microsilica	M-sand
	(In kg/m^3)				
SCC60CC	450	60	120	50	836
SCC60Hy1	450	60	120	50	836
SCC60Hy2	450	60	120	50	836
SCC60Hy3	450	60	120	50	836
SCC60Hy4	450	60	120	50	836
SCC60Hy5	450	60	120	50	836
SCC60Hy6	450	60	120	50	836
SCC60Hy7	450	60	120	50	836
SCC60Hy8	450	60	120	50	836
SCC60Hy9	450	60	120	50	836
SCC60Hy10	450	60	120	50	836
SCC80CC	450	200	0	50	874
SCC80Hy1	450	200	0	50	874
SCC80Hy2	450	200	0	50	874
SCC80Hy3	450	200	0	50	874
SCC80Hy4	450	200	0	50	874
SCC80Hy5	450	200	0	50	874
SCC80Hy6	450	200	0	50	874
SCC80Hy7	450	200	0	50	874
SCC80Hy8	450	200	0	50	874
SCC80Hy9	450	200	0	50	874
SCC80Hy10	450	200	0	50	874

Table 2. Mix proportions used in this study (Part-2)

Mix ID	Coarse aggregate	Water	Super-plasti-ciser	Hooked-end steel	Micro-steel
	(In kg/m^3)				
SCC60CC	694	190	4.42	0	0
SCC60Hy1	694	190	6.05	23.55	15.7
SCC60Hy2	694	190	6.46	31.4	7.85
SCC60Hy3	694	190	6.19	27.475	11.775
SCC60Hy4	694	190	5.44	19.625	19.625
SCC60Hy5	694	190	5.3	15.7	23.55
SCC60Hy6	694	190	5.64	11.775	27.475
SCC60Hy7	694	190	5.1	7.85	31.4
SCC60Hy8	694	190	7.48	39.25	19.625
SCC60Hy9	694	190	6.8	31.4	27.475
SCC60Hy10	694	190	6.66	19.625	39.25
SCC80CC	669	190	4.69	0	0
SCC80Hy1	669	190	6.37	23.55	15.7
SCC80Hy2	669	190	6.72	31.4	7.85
SCC80Hy3	669	190	6.23	27.475	11.775
SCC80Hy4	669	190	5.46	19.625	19.625
SCC80Hy5	669	190	5.32	15.7	23.55
SCC80Hy6	669	190	5.74	11.775	27.475
SCC80Hy7	669	190	5.11	7.85	31.4
SCC80Hy8	669	190	8.05	39.25	19.625
SCC80Hy9	669	190	7.7	31.4	27.475
SCC80Hy10	669	190	6.79	19.625	39.25

4 Results and Discussions

PREDICTION OF COMPRESSIVE STRENGTH WITH DATASET

The suggested model was tested using four datasets, including data sets 1 (9 parameters), 2 (6 parameters), 3 (6 parameters), and 4 (6 parameters), that were gathered from the body of existing literature. Six input factors from the experimental results of Prasad et al. (2009) and Patel et al. (2004) served as the input data for the model that predicted compressive strength. Table 3 contains a tabulation of the input parameters, experimental compressive strength, anticipated compressive strength, and % error. A portion of the data set 20% for testing and 80% for training was kept aside. To create the validation dataset, random samples are chosen from the complete dataset.

It was discovered that the compressive strength in accuracy percentage ranged from 0.006 to 20.166%. The training process of the ANN regression model is shown in Figure 3 along with validation failure (training error), gradient, and Mμ. At the 13th epoch, the values of gradient, Mμ, and validation check were found to be 0.26293, 10–11, and 6. The regression plot for the training, testing, validation, and all datasets is displayed in Figure 2. The R2 values for all datasets, testing, validation, and training were 0.98817, 0.30817, 0.89532, and 0.9154, in that order.

When creating a regression line using the equation Y=T, where Y represents the coordinate of the y-axis and T denotes the position of the x-axis, the majority of the data points are fitted to the corner of the regression line with excellent R2 values. The regression curve for the training, testing, and validation datasets is shown in Figure 2. Epoch 7 yielded the best validation performance, with a value of 25.5933, thanks to the JO algorithm's optimum training of the m Sigmoid-ANN model. The majority of the data points are on the regression line, which has the same equation for the training and all data sets.

The remaining data points, however, fall in the vicinity of the regression line, whereas the testing and validation data points lie on it. Therefore, using the chosen set of characteristics, the proposed model's prediction of compressive strength performs well for the SCC. Testing, training, and validation MSE curves decrease until the sixth epoch and then stay constant for the remaining epochs.

The creation and use of the prediction model for the mechanical characteristics of 60 MPa and 80 MPa SCC concrete with the inclusion of hybrid steel fibres at the ratio of 0.5% hooked-end and 0.75% micro-steel fibres was described in this study. The prediction model used the innovative JO-m Sigmoid-ANN. Using experimental data and four distinct datasets (datasets 1, 2, 3, and 4) the suggested model was verified. In comparison to the other datasets, the suggested model demonstrated an enhanced prediction performance in the range of 0.01–15.56%. Only the data set 1 results were shown here in Fig.2 &3 below.

Table 3. Actual and predicted compressive strength for dataset-1

Cement(kg/m^3)	Fly ash(kg/m^3)	Water/powder	SP (%)	Sand (kg/m^3)	Coarse aggregate (kg/m^3)	Reference target compressive strength	Achieved output	Percentage error (%)
220	180	0.39	0.35	916	900	49	47.47	3.21
220	180	0.39	0.35	916	900	49	47.47	3.21
160	240	0.39	0.35	886	900	44	43.97	0.05
193	158	0.39	0.35	1024	900	44	43.99	0.01
220	180	0.45	0.35	850	900	38	31.62	20.16
198	232	0.34	0.2	874	900	46	51.88	11.33
248	203	0.39	0.35	808	900	50	49.95	0.08
237	133	0.36	0.2	1034	900	49	49.02	0.04
220	180	0.39	0.35	916	900	49	47.47	3.21
237	133	0.43	0.5	960	900	46	45.93	0.14
275	155	0.43	0.5	827	900	48	48.00	0.01
280	120	0.39	0.35	946	900	45	51.47	12.5
170	200	0.43	0.2	930	900	31	31.03	0.11
220	180	0.39	0.6	916	900	43	42.90	0.23
220	180	0.39	0.35	916	900	47	47.47	1.00
220	180	0.39	0.1	916	900	44	44.16	0.379
198	232	0.36	0.5	872	900	52	50.51	2.93
220	180	0.39	0.35	916	900	45	47.47	5.21
220	180	0.33	0.35	982	900	51	50.98	0.03
170	200	0.43	0.5	928	900	33	32.98	0.04
275	155	0.43	0.2	830	900	36	37.23	3.31

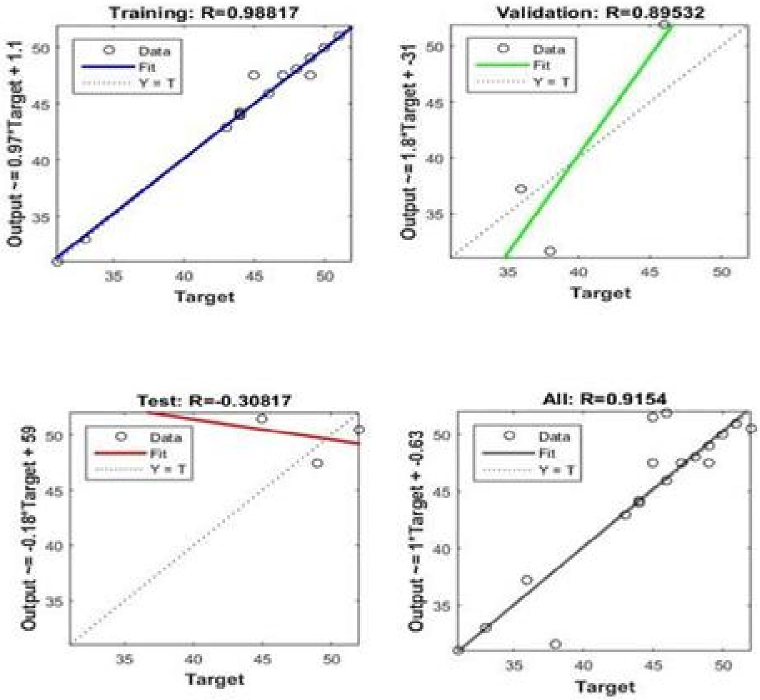

Fig2. Regression plots of ANN

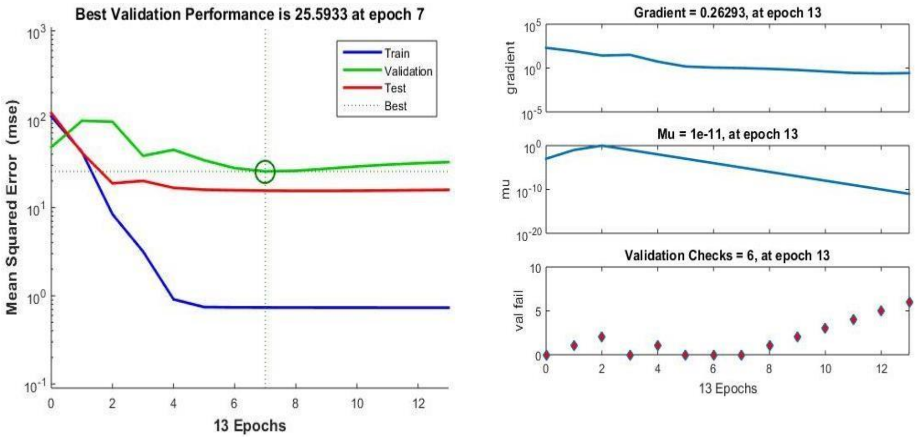

Fig.3. Training state of ANN & performance on dataset 1

5 Conclusion

GENERAL

The use of mixed hooked-end and straight steel fibres in SCC to create high-performance fibre-reinforced SCC is the study's main breakthrough. It has been demonstrated that the hybrid steel fibre reinforcement enhances the SCC concrete's flexural and shear properties. Additionally, the durability and workability of the concrete mix were enhanced by the addition of several admixtures, including fly ash, micro-silica, and GGBS. Utilising an artificial neural network (ANN) model to forecast the characteristics of HFRSCC is another novel approach in this research.

A technique for machine learning that can be trained to understand the link between a set of input parameters and a set of output parameters is called an artificial neural network (ANN). The amount of cement, fly ash, GGBS, micro-silica, M-sand, coarse aggregate, water, super-plasticizer, micro-steel, and hooked-end steel fibres were among the input characteristics taken into account.

The characteristics of the HFRSCC mix, both fresh and hardened, were the output parameters. For M60 and M80 grade SCC, a mix design for high performance HFRSCC was created. For concrete with 60 and 80 MPa, about ten distinct HFRSCC mixes were created by using hybrid fibres at varied volume fractions. After 28 days, the mixes were adjusted to achieve the desired strengths of 60 and 80 MPa for the HFRSCC and ordinary mixes, respectively.

ANN PREDICTION MODEL

With R2 values of 0.9679 and 0.9931 for the test data gathered from the experimental investigation, the JO m Sigmoid-ANN was utilised to predict the strength parameters such as compressive strength, split tensile strength, flexural strength, and elastic modulus. The suggested model was tested using four datasets, including data sets 1 (9 parameters), 2 (6 parameters), 3 (6 parameters), and 4 (6 parameters), that were gathered from the body of existing literature. The present data sets 1, 2, 3, and 4 have calculated R2 values of 0.9868, 0.9164, 0.9338, and 0.74619, respectively. The results indicated that the suggested model outperformed data sets 1, 3, and 4 by 9%, 0.01%, and 15.56%, respectively.

In comparison to the current models, it can be concluded that the suggested JO-m Sigmoid-ANN prediction framework performs better in the prediction of flow and strength properties of steel fibre-incorporated SCC.

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