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# Prediction of Strength and Fresh Properties of Steel Fiber Reinforced Self Compacting Concrete Using Artificial Intelligence Approach

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## Abstract

Concrete utilization is increased with the rapidly growing construction industry, compaction is the main exertion that arisen in the concrete. Self-compacting concrete (SCC) is a flowable concrete that can flow under its own weight in the congested reinforcements without any need for external vibration. As the lesser usage of aggregates leads to the decrease in stiffness of SCC which may cause the earlier formation of cracks, adding fibers increase the stiffness of SCC, and also it has a lot of consequences for finding out fresh and mechanical properties. This study mainly focuses on the application of Artificial Neural Networks (ANN) to predict the fresh and mechanical properties of steel fiber reinforced SCC. In the proposed model nine input parameters and seven output parameters are considered for modeling. For training and testing of the data along with regression analysis was performed using MATLAB using the ANN tool. It is used for the complete modeling and one hidden layer and ten neurons and 1000 epochs. The model performance was evaluated based on three metrics sets which includes correlation coefficient ($R^2$), root mean square error (RMSE) and mean absolute percentage error (MAPE). The obtained correlation coefficient value will be between 0.9 and 1, which implies good accuracy of prediction.

## Keywords

Artificial neural network, Self-compacting concrete, Steel fibers, Regression analysis, Nanotechnology

## Introduction

Concrete is a key building material that has historically proved useful all over the world. Around the world, especially in the industrial regions, there has been a significant increase in the usage of concrete. For the incorporation of nanoparticles in nanofibers, three main techniques were identified. The most commonly mentioned one is direct blending electrospinning, where the nanoparticles are encapsulated and/or entrapped in the nanofibers [1, 2]. Now, in present days there is an alternative for the usage of conventional concrete in regard to it saves time as well as better quality in both fresh and hardened states. The alternative and new construction material is SCC. SCC is one of the novel concrete varieties that has recently seen widespread use. The development of SCC, among other trends and advancements in the construction sector, offers a standard potential and attractive interest to use secondary raw materials and byproducts as mineral additives (fly ash, GGBS, metakaolin, etc.) [3-5]. SCC is also acknowledged as self-consolidated concrete which eliminates the compaction of concrete without vibration and not affecting its engineering properties. SCC was developed to reduce the cost of skilled labor, manpower and eliminates the compaction problems. SCC avoids noise pollution due to vibration by compacting itself. In addition, nanofibers can be prepared using various polymers such as keratin, collagen, silk fibroin, cellulose, gelatin, poly(lactic acid), poly(lactic-co-glycolic acid), poly(ethylene-co-vinylacetate), and polysaccharides such as alginate and chitosan [6, 7].

In order to achieve good properties of SCC, few properties are to be achieved i.e., ability to fill, ability to pass and segregation resistance. The lower content of aggregates makes the concrete lesser stiff. The tensile strength of the concrete is very less compared to that of the compressive strength, for enhancing the tensile properties fibers are supplemented to the concrete [8]. The usage of steel fiber reinforced SCC has been increased in construction due to its various advantages. Fiber increases the toughness, flexural strength and also helps in resistance against cracking of the concrete. Testing of fresh and hardened properties for finding out the properties of the concrete as per conventional methods is time consuming [9]. As an alternate method for finding the properties of concrete soft computing techniques were used in order to save time. ANN, a soft computing technique is used to predict the fresh and hardened properties of SCC. The structure of nanofibers depends on the type of precursor used, and the method of production allows for controlling the shape and arrangement of nanofibers. The most common structures of nanofibers were hollow, mesoporous, nonporous, and core-shell types of nanofibers. Many researchers used the applications of ANN in various concrete like light weight concrete, conventional concrete and geopolymer concrete.

Verma et al. [10] has carried research on geopolymer concrete using fly ash by using ANN model from MATLAB for prediction of compressive strength by varying the parameters such as properties of fly ash, curing temperature, curing time and alkaline concentration solution and liquid to fly ash ratio. The researcher concluded that ANN model is efficient in predicting compressive strength with $R^2$ of 0.85. Yan et al. [11] focused on predicting hysteretic performance of composite reinforced concrete beam using ANN, for predicting shear and flexural behavior of steel fiber reinforced concrete beams for different fiber dosages varying from 0.1 to 5% per volume, stirrups and steel reinforced bars and concluded that cyclic efficiency in measuring deformation and energy calculations. The results state that the usage of ANN has the feasibility for predicting the properties of concrete. The study conducted by Shi et al. [12] on concrete fatigue life prediction model based on the ANN model by using GRW-DBA methods for enhancing the accuracy of the prediction. Extended research on waste foundry sand for developing sustainable concrete was carried out by Golafshani et al. [13], on predicting the mechanical properties based on ANN model aided by MOMVO algorithm. A review on predicting mechanical properties of recycled concrete based on artificial intelligence algorithms and its accuracy was studied by Nguyen et al. [14]. For the present study predicting the fresh and hardened properties of steel fiber reinforced SCC using ANN was carried out. The research mainly focused on the data collection of the SCC and processing the data for the best model to predict the properties of steel fiber reinforced SCC.

# Experimentation

### ANN

The algorithms that can pretend the functioning of the human brain are ANNs. ANN comprehends input layer, hidden layer, and output layer. In which input layer has input neurons and hidden layer have hidden neurons and output layer have output neurons. Each neuron in the input layer is connected with each neuron in the hidden layer, which can lead to the formation of an effective neural architecture. To train the neural network, the processing of the output network needs to be compared for predicting the desired output. The neurons help to adjust weights in between the layers without any convergence and help to obtain better prediction results. This complete process is going on in a neural net. Figure 1 represents the representation of ANN architecture.

### Feed forward neural network

One of the easiest types of neural network is feed forward neural network. For this study network modeling is carried out using the Feedforward back propagation technique, in which the signals are forwarded for the respective epoch after that they will be propagated backward. This process will continue for the given number of epochs, through this error will be minimized. In this study, 1000 epochs will be given to model the ANN, and Levenberg-Marquardt backpropagation algorithm is used.

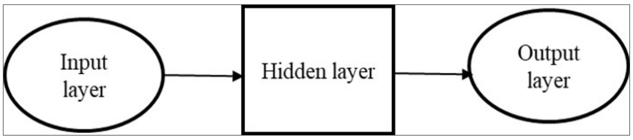


**Figure 1:** Simple representation of architecture of ANN.

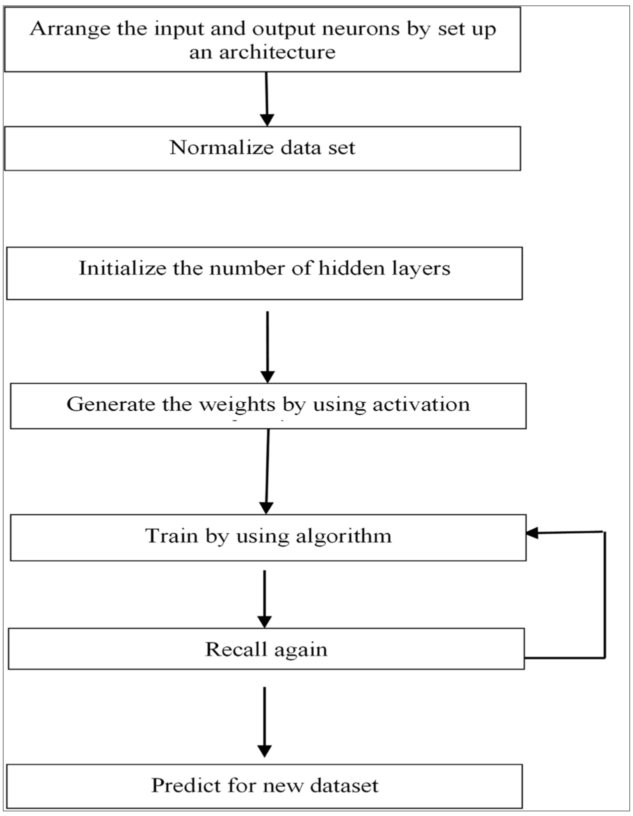


**Figure 2:** Schematic of neural network architecture.

Figure 2 represents the schematic architecture of feed forward backpropagation ANN. Let assume ($a_1$, $a_2$, $a_3$, ……, $a_n$) are the input parameters and weights are represented in ($W_{k1}$, $W_{k2}$, $W_{k3}$, ……., $W_{kn}$) these weights are adjusted in the hidden layer for the $K^{th}$ neuron. Where $Y_k$ is the neuron output, summation function is used to quantify the weights and complete process is carried out with the help of activation function. Figure 2 characterizes the schematic neural network architecture.

Equation 1 and 2 represents the summation of input 1 and input 2 for the $K^{th}$ neuron. Equation 3 represents the summation for $i^{th}$ input.

$$v_1 = a_1 W_{1k} + b_k \tag{1}$$

$$v_2 = a_2 W_{2k} + b_k \tag{2}$$

$$v_k = \sum_{i=1}^{n} a_i W_{ik} + b_k \tag{3}$$

Where f is the transfer function, f is the activation function and $b_k$ is the bias function. Equation 4 characterizes the output function for all the neurons.

$$Y_k = f(v_k) = f\left(\sum_{i=1}^{n} a_i W_{ik} + b_k\right) \tag{4}$$

## Network methodology

Network methodology starts with arranging input and output neurons in the layers. Normalization of data will be carried out between 0 and 1. Figure 3 characterizes the procedure of ANN in the steps.

Before going into modeling, hidden layers count and hidden layers count were selected. After arranging all the neurons in a requisite format modeling will be started. ANN modeling includes three phases that are network training, testing and validation.

## Collection of data

For the present study, mix values are collected from the various previous literature. A series of data with a total number of 50 were collected. The input parameters and output parameters are selected in a way that gets better prediction accuracy. In this study not only mechanical properties also fresh properties were predicted. As SCC was defined by its fresh properties, workability is the main property of SCC, and the main tests to find the fresh properties are difficult to conduct. From the total amount of data, around 70% of data will be used for training and 30% of data will be used for testing. A larger amount of data will be used for training because the software learns from this data after all it predicts very accurately. Table 1 and table 2 represent the list of input and output variables used in this study.

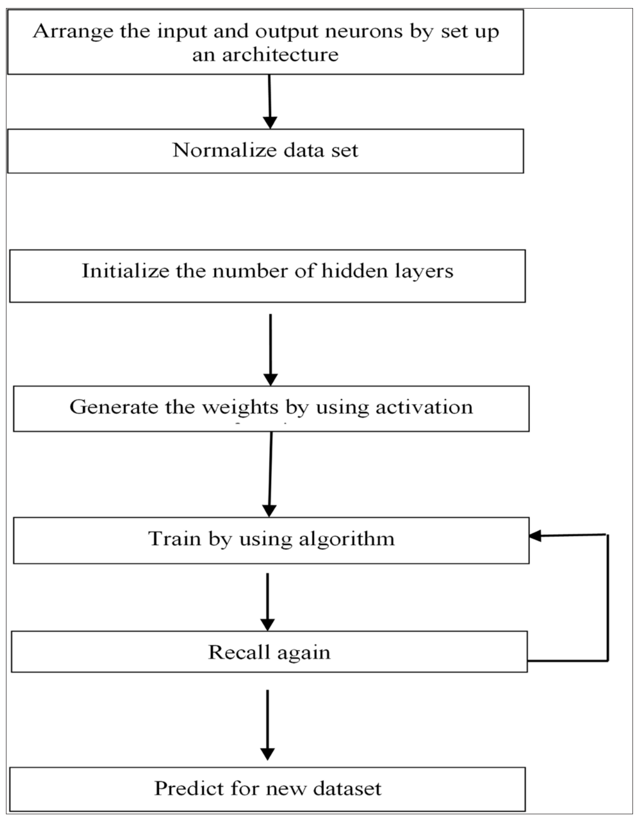


**Figure 3:** The stepwise procedure of ANN.

## Modelling ANN

For training and testing of the data along with regression analysis was performed using MATLAB using the ANN tool. Complete modeling will be based on three steps. The three main steps are training, testing, and implementation. The model will be trained with the given number of inputs then after the weights are adjusted for training and, in the testing, the prediction will be carried out without clustering the data.

**Table 1:** Number of mixes of input variables.

| S. No. | Fly ash | Cement | Fine aggregate | Coarse aggregate | Aspect ratio | Volume fraction | Water | Super plasticizer | Curing days |
|---|---|---|---|---|---|---|---|---|---|
| | (Kg/m³) | (Kg/m³) | (Kg/m³) | (Kg/m³) | (Kg/m³) | (%) | (Kg/m³) | (%) | - |
| **Mix 1** | 210 | 390 | 748.79 | 782.55 | 15 | 0.5 | 186 | 2.99 | 7 |
| **Mix 2** | 210 | 390 | 742.14 | 775.60 | 15 | 1 | 186 | 2.96 | 7 |
| **Mix 3** | 225 | 339 | 554 | 1000 | 60 | 1 | 214 | 1 | 28 |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Mix 48** | 150 | 500 | 840 | 675 | 35 | 0.5 | 202.5 | 4.5 | 7 |
| **Mix 49** | 189 | 425 | 625 | 1270 | 35 | 1 | 220 | 2.12 | 7 |
| **Mix 50** | 106 | 424 | 768 | 668 | 15 | 1 | 220 | 4.5 | 28 |

**Table 2:** Number of mixes of output variables.

| S. No. | Compressive strength | Split tensile strength | Flexural strength | Slump flow | V funnel | L box | J-ring |
|---|---|---|---|---|---|---|---|
| | ($N/mm^2$) | ($N/mm^2$) | ($N/mm^2$) | (mm) | (sec) | - | (mm) |
| **Mix 1** | 36.32 | 4.22 | 8.34 | 685 | 7.4 | 0.88 | 8 |
| **Mix 2** | 37.11 | 4.42 | 8.41 | 660 | 8.5 | 0.82 | 6 |
| **Mix 3** | 54.85 | 5.4 | 7.69 | 675 | 8 | 0.82 | 6 |
| --- | --- | --- | --- | --- | --- | --- | --- |
| --- | --- | --- | --- | --- | --- | --- | --- |
| **Mix 48** | 3954 | 4.72 | 8.36 | 720 | 9 | 0.82 | 10 |
| **Mix 49** | 36.45 | 4.78 | 8.7 | 700 | 8.7 | 0.98 | 10 |
| **Mix 50** | 69.98 | 4.42 | 6.95 | 680 | 8 | 0.88 | 9 |

**Table 3:** Input and output variables used in ANN model.

| Variables | Range |
|---|---|
| Aspect ratio ($Kg/m^3$) | 0 - 60 |
| Volume fraction (%) | 0 - 15 |
| Fly ash ($Kg/m^3$) | 0 - 390 |
| Cement ($Kg/m^3$) | 237 - 500 |
| Water ($Kg/m^3$) | 142 - 214 |
| Fine aggregate ($Kg/m^3$) | 517 - 783.14 |
| Coarse aggregate ($Kg/m^3$) | 113 - 1188.34 |
| Super plasticizer (%) | 0 - 7.5 |
| Slump flow (mm) | 0 - 735 |
| V funnel (sec) | 0 - 12 |
| L box ratio | 0 - 0.98 |
| J ring (mm) | 0 - 10 |
| Compressive strength ($N/mm^2$) | 30.02 - 72.32 |
| Split tensile strength ($N/mm^2$) | 3.8 - 7.24 |
| Flexural strength ($N/mm^2$) | 5.6 - 27.57 |

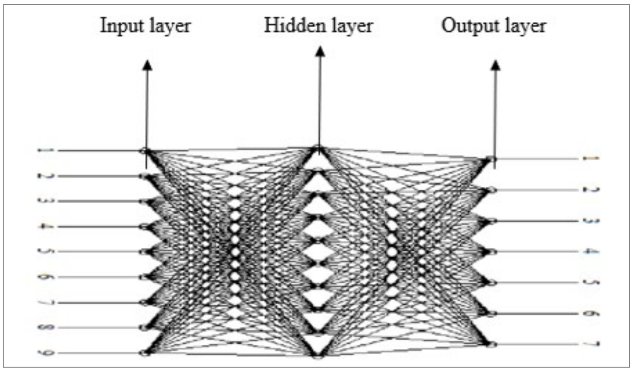


**Figure 4:** Neural network model.

In the present study, a model will be developed by considering nine input parameters and seven output parameters, and the number of input and output variables are represented in table 3. The neurons count in the hidden layer will be 10, and the neurons count in the output layer will be 7. These input and output neurons are represented in figure 4. For the given neurons modeling will be carried out for the epochs. Using the feedforward backpropagation technique complete modeling is carried out for the given number of epochs. Table 3 represents the range of input and output variables used in this study. In this study, modeling was done with the help of one hidden layer, ten neurons and 1000 epochs. The model performance was evaluated based on three metrics sets which includes $R^2$, RMSE and MAPE.

Some parameters are needed to model the ANN, complete modeling will be carried out in MATLAB using the ANN tool. In this study, 1000 epochs will be used in modeling in both the training and testing phase. As for the backpropagation technique for epoch, the signals will be sent forward and errors will be propagated backward like this the overall error will be reduced. Table 4 characterizes the parameters used in the modeling of ANN.

**Table 4:** Parameters used in the modeling of ANN.

| Variables | Values |
|---|---|
| Input parameters count | 9 |
| Output parameters count | 7 |
| Hidden layers count | 1 |
| Neurons count in the hidden layer | 10 |
| Rate of learning | 1 |
| Momentum coefficient | 0.01 |
| Average error per output per dataset | 0.005 |
| Epochs | 1000 |

Figure 4 represents the network model of ANN which is modeled in MATLAB. In these 9 inputs are connected to the input layer, these inputs are related with the 10 neurons in the hidden layer. Also, 7 output neurons are connected with the output layer.

## Results and Discussion

The steel fiber reinforced SCC is considered in the study to predict the fresh and hardened properties. The data is collected from the literature and the data is segregated and processed for analysis. In the process of analysis, the data is given for both testing and validation. 85% of the test data from literature is

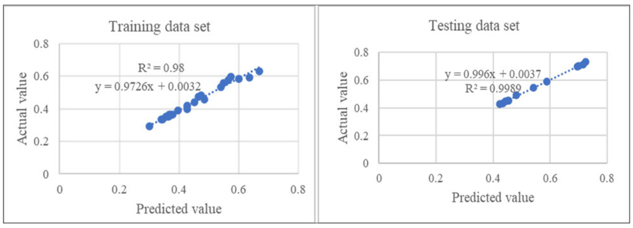


**Figure 5:** Training and testing dataset regression model for compressive strength.

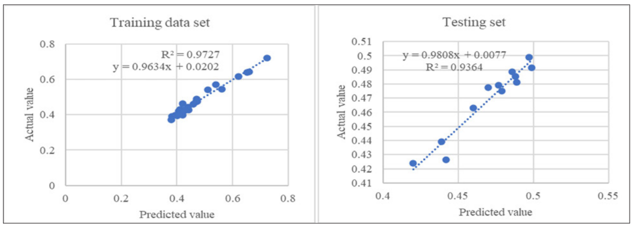


**Figure 6:** Training and testing dataset regression model for split tensile strength.

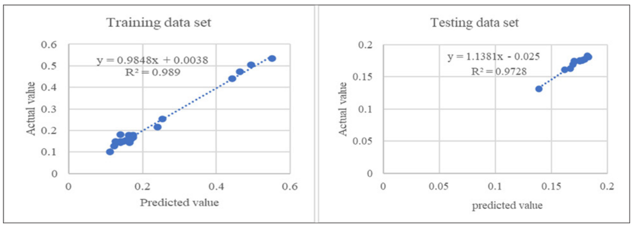


**Figure 7:** Training and testing dataset regression model for flexural strength.

used for testing and 15% is used for validating the test results. The regression analysis is done for representing the correlation between input and output parameters. The input parameters considered in this study were cement, fine aggregate, coarse aggregate, water, and steel fiber quantities were given to predict the fresh and hardened properties of steel fiber reinforced SCC. The fresh properties are identified through the slump test, J ring test, V funnel and L box tests. The predicted values are shown in figure 5 to figure 7 of hardened properties. The model performance was evaluated based on three metrics sets which includes $R^2$, RMSE and MAPE. The regression result is shown in the below figures for training and prediction tests for all the parameters. It represents the best correlation between input and output. The predicted values of fresh properties from slump test, J ring test, V funnel and L box tests are shown in figure 8 to figure 11. The output parameters were hardened properties such as compressive strength, split tensile strength and flexural strength. Figure 5 to figure 11 represent the regression curves for training and testing data.

The graphs (Figure 5 to figure 11) for testing and testing data set for hardened properties were plotted between the foreseen and actual values. The $R^2$ value is 0.98 for training data set and 0.99 for testing data of compressive strength test which reflect that the testing data and training data are correlating with each other. The $R^2$ value is 0.97 for training data set and 0.93 for testing data of split tensile strength which reflect that the testing data and training data are correlating with each other. The $R^2$ value is 0.98 for the training data set and

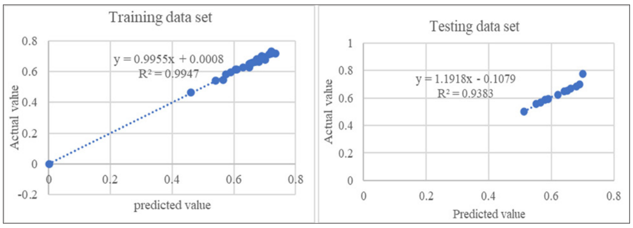


**Figure 8:** Training and testing dataset regression model for slump test.

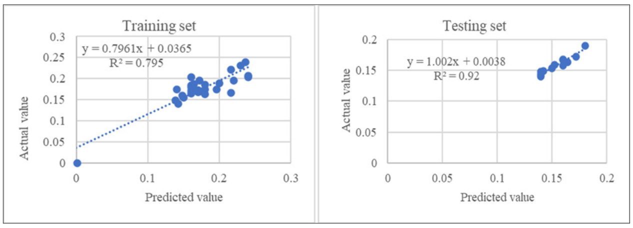


**Figure 9:** Training and testing dataset regression model for V funnel test.

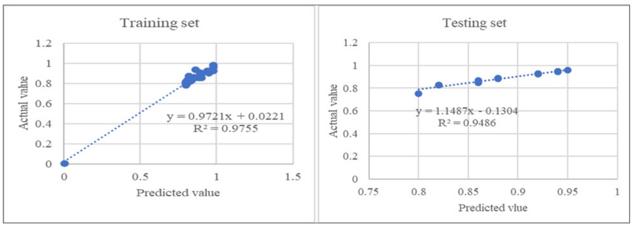


**Figure 10:** Training and testing dataset regression model for L box test.

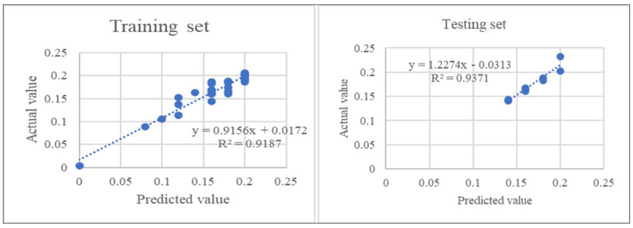


**Figure 11:** Training and testing dataset regression model for J ring test.

0.97 for testing data of flexural strength test which reflect that the testing data and training data are correlating with each other. The $R^2$ value is 0.98 for training data set and 0.97 for testing data of slump test which reflect that the testing data and training data are correlating with each other. The $R^2$ value is 0.99 for the training data set and 0.93 for testing data for V funnel test which reflect that the testing data and training data are correlating with each other. The $R^2$ value is 0.97 for training data set and 0.94 for testing data which reflects that the testing data and training data for L box test are correlating with each other. The $R^2$ value for training data set is 0.91 and 0.93 for J ring test which reflects that the testing data and training data are correlating with each other.

The input parameters were chosen in a way that includes all necessary data to produce the desired result. For the modelling in this work, 9 input parameters and 7 output parameters were used. These parameters are shown in table 1. Processes for training, validating, and predicting are used. To verify the effectiveness of ANN, three metrics—$R^2$, MAPE, and RMSE were utilised. Equation 5, 6, and 7 are used to calculate these

**Table 5:** Characterizes the values of the statistical parameters of models.

| Models | $R^2$ | | MAPE | | RMSE | |
|---|---|---|---|---|---|---|
| | Training | Testing | Training | Testing | Training | Testing |
| Compressive strength | 0.98 | 0.99 | 0.583 | 0.412 | 0.998 | 0.993 |
| Split tensile strength | 0.97 | 0.93 | 0.601 | 0.842 | 1.023 | 1.995 |
| Flexural strength | 0.98 | 0.97 | 0.562 | 0.463 | 0.998 | 1.059 |
| Slump test | 0.99 | 0.93 | 0.102 | 0.932 | 0.996 | 2.013 |
| V funnel test | 0.8 | 0.92 | 1.023 | 0.889 | 4.231 | 2.694 |
| L box test | 0.97 | 0.94 | 0.489 | 0.551 | 0.987 | 1.015 |
| J ring test | 0.91 | 0.93 | 0.918 | 0.617 | 3.023 | 1.023 |

three metrics.

$$R^2 = \left( \frac{\sum_{i=1}^{n} (P_i - Q_i)^2}{\sum_{i=1}^{n} Q_i^2} \right) \quad (5)$$

$$MAPE = \frac{1}{n} \sum_{i=1}^{n} \left| \frac{P_i - Q_i}{P_i} \right| \text{ x } 100 \quad (6)$$

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^{n} (P_i - Q_i)^2} \quad (7)$$

Where, n is number of data sets used in training and testing phase, $P_i$ is the value of actual strength, and $Q_i$ is the value of predicted strength values.

From table 5 observed the obtained $R^2$ value will be between 0.9 and 1, which indicates the weights are adjusted in between the layers and neurons. Each parameter predicted well obtained very good prediction accuracy. For all the parameters obtained error will be very less because of the use of the feed forward neural network technique. The obtained MAPE and RMSE values are very less for all parameters which indicate good agreement between input and output variables.

## Conclusions

This study mainly focuses on the development of a prediction model in order to predict the fresh and mechanical properties of steel fiber reinforced SCC based on the application of ANN. The proposed model takes into account of nine input parameters and seven output parameters to develop the neural network. For training and testing of the data along with regression analysis was performed using MATLAB using the ANN tool. In this study, modelling was done with the help of one hidden layer, ten neurons and 1000 epochs. The model performance was evaluated based on three metrics sets which includes $R^2$, RMSE, and MAPE.

- This study provides a beneficial method for predicting the compressive strength of SCC with steel fiber reinforcement.
- From this study, the obtained statistical parameter $R^2$ for compressive strength is 0.98, 0.99 for training and testing steps, respectively.
- The obtained $R^2$ value is between 0.9 and 1, which implies good accuracy of prediction.
- RMSE and MAPE values are 0.053 and 0.998 for compressive strength and for all the parameters it shows less than zero, which means they obtained error is very less.
- Further, time can also be saved, and also huge amounts of materials required for conducting tests can be saved.
- Hence, ANN can perfectly and confidently be assured for the prediction of mechanical and fresh and hardened properties of SCC.

This study presents a preliminary investigation and prediction model for SCC with particular combinations of input and output parameters. Further, this study can be extended to a detailed investigation including many other parameters can be performed to develop a parametric prediction model, which can be used for various applications.

## Acknowledgements

None.

## Conflict of Interest

None.

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