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Prediction of Mechanical and Tensile Properties of Self-Compacting Concrete Incorporating Fly Ash and Waste Copper Slag by Artificial Neural Network-ANN

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ABSTRACT

Self-compacting concrete (SCC) is a specialized form of concrete known for its exceptional workability, high paste content, and incorporation of cement substitutes like silica fume, natural pozzolana, and slag. These cement alternatives offer various advantages including cost reduction, decreased carbon dioxide emissions, reduced depletion of natural resources, and enhanced properties in both fresh and hardened states. SCC finds application in diverse scenarios such as structures with densely packed reinforcement and tall shear walls, necessitating accurate performance prediction. This study aims to develop artificial neural network (ANN) models for forecasting the compressive strength, split tensile strength, and flexural strength of self-compacting concrete incorporating fly ash and waste copper slag, assessed at curing periods of 7, 28, 56, and 90 days. The ANN model comprises several input and output parameters, with model accuracy evaluated using Mean Squared Error (MSE) and R-squared (R^2) metrics. Furthermore, the network's performance is evaluated through error histograms and regression network predictions using ANN. The Levenberg-Marquardt optimization method, implemented in MATLAB 2020a, is employed to effectively estimate the compression strength, split tensile strength, and flexural strength of self-compacting concrete, ensuring reliable results.

1. INTRODUCTION

Concrete is a popular building material with many benefits; thus, its mechanical properties are crucial for structure design. The structure's compressive strength is most important since it dictates its safety and performance throughout time [1-16]. Self-compacting concrete contains aggregates, cement, and other components randomly distributed throughout the matrix. The complexity of building components complicates concrete compressive strength estimate. Many variables affect the technical properties of cement-based products and special purpose concretes. They vary because they have varied materials, characteristics, and certain components impact concrete performance in three or more ways. To utilize these materials in various constructions, you must understand their behavior. In order to study the impact of these parameters and forecast concrete's compressive strength, several statistical models and methods have been created, drawing on data from both laboratory experiments and field trial testing. It is expensive, takes a long time, and requires a lot of work. Also, the accuracy of the predictions relies a lot on the skills of the people working there and the quality of the labs [17-23].

Changing the mix quantities may prevent concrete from failing or becoming excessively strong. This is conceivable if concrete compression strength can be calculated promptly. This lower building expenses by reducing material prices and construction errors.

The use of Machine Learning (ML) models, a relatively new but rapidly improving tool that mimics human intelligence in solving complex problems, proved to be a simpler, more efficient, and more accurate way to forecast concrete compressive strength than the time-consuming and costly methods previously used in laboratories. Several machine learning methods, including ANN and SVM models, have shown exceptional generalizability and prediction capabilities when applied to a variety of difficult nonlinear issues. Moreover, both models have been shown to accurately estimate concrete strength, according to the literature, surpassing previous regression-based models. There have been a number of studies that used ML algorithms to better estimate the compressive strength of various concrete kinds. With reference to Al-Jamimi et al. [23], the experimental findings showed that the suggested model might be useful for predicting concrete compression strength, with correlations of R^2=0.99 attained during testing. Additionally, the experimental findings show that the projected values derived from the model (SVM-GA) closely match the actual data with an RMSE of 0.002.

Verma et al. [24] explains utilizing an artificial neural network (ANN) to estimate geopolymer concrete compressive strength using experimental data. The MATLAB-modeled ANN predicts compressive strength using the input parameter. This study illuminates how curing temperature and duration affect geopolymer concrete compressive strength. With R^2 = 0.85, the ANN model predicted compressive strength well. el Asri et al. [25] describes in detail the use of artificial neural networks to the problem of modeling the compressive strength of SCC after 28 days after loading. The model is based on rheological data measured in empirical experiments, such as the V-Funnel flow duration, the plastic viscosity, and the yield stress, as well as the lump flow diameter and H2/H1 ratio of the L-Box. This work aims to identify the best model for modeling compressive strength using numerical and experimental analysis. Following many model trainings, it was determined that a 5-50-50-1 architecture with a Pearson's correlation R = 97.58% was the most effective. Zhao et al. [26] investigates two ANN-based scenarios to eke out the uniaxial CS of MSC. According to the first scenario, normal trainer Levenberg-Marquardt is the most powerful. Both BBO and MTOA were able to generate a more accurate ANN when compared to the CNN's performance using hybrid models. By using the BBO during training, the CNN's root mean square error was reduced by 8 [27]. The purpose of this research is to 77%, and by using the MTOA during testing, it was reduced by 11.46%. Consequently, the proposed hybrids may serve as viable substitutes for conventional models in the prediction of concretes. Trilok Gupta et examine the impact of the input parameters on the output parameters by attempting to build explicit expressions using an artificial neural network (ANN) technique. Results show that w=c, RF, T, and t each contribute an average of 6.67%, 10.10%, 80.01%, and 3.22% to the final output measure, respectively. Out of all the input factors, T has the greatest effect on the output parameters, followed by RF, while the other input parameters (w=c; t) have comparatively lesser effects. The current research presents a novel method that utilizes artificial neural networks to get the FRP constrained compressive strength of concrete from a huge amount of experimental data [28]. The FRP-confined compressive strength of concrete was the output node after inputs like concrete and FRP properties were inputted into the ANN model. We used the idealized neural network to generate design-related empirical charts and equations. The produced ANN-based model accurately predicts the FRP-confined compressive strength of concrete, as shown by comparisons with both existing experimental and empirical data and the novel method. To forecast the compressive strength of silica fume concrete, artificial neural networks (ANN) and fuzzy logic (FL) were implemented in this research [29]. In the ANNs and FL investigation, a data set from a laboratory experiment involving the production of forty-eight distinct types of concrete was utilized. The parameters of the concrete mixture comprised three partial silica fume replacement ratios, four distinct water–cement ratios, and three distinct cement concentrations. The compressive strength of specimens that had been moist-cured was assessed at five distinct time points. The outcomes derived from the experimental methodologies were juxtaposed with those obtained from ANN and FL. As demonstrated by the outcomes, ANN and FL may serve as viable substitute methods for forecasting the compressive strength of silica fume concrete. A new artificial neural network (ANN) model using the Levenberg-Marquardt back propagation method with 366 experimental trials predicts SCC compressive strength with silica fume [30]. Using a nonlinear connection with components, the model correlated with SCC compressive strength (output). The model's predictions and actual data from other studies showed significant agreement to evaluate its predictive power and applicability. Parametric analysis was done to assess the ANN suggested model's sensitivity to water-to-binder ratio and superplasticizer concentration. A strong correlation value R^2=0.93 suggests that this study's model may predict SCC compressive strength with good results. The model is simple and effective. An investigation was conducted to compare the accuracy of machine learning algorithms in predicting the compressive strength of concrete at 28, 56, and 91 days of age, using the "R" software environment [31]. As a vital tool for academics, R is firmly establishing itself in the statistical field. This data set was created in a controlled environment. This study used R miner to compare three popular data mining models: the decision tree (DT) model, the random forest (RF) model, and the neural network (NN) model. The results showed that the NN model had the best predictive power for the compressive strength of concrete, with R^2 and RMSE serving as the primary metrics for accuracy. The civil engineering field places a premium on the ability to predict the compressive strength of concrete [32]. This study finds the best values for the parameters of a multi-layer perceptron (MLP) neural processor using two new optimization methods: the equilibrium optimizer (EO) and the evaporation rate-based water cycle algorithm (ER-WCA). The ER-WCA optimizer improved the MLP's training accuracy by 11.18%, while the EO optimizer improved it by 3.1% (in terms of minimizing the root mean square error). The results of the tests also showed an increase in correlation, going from 78.80% to 82.59% and 80.71%, respectively. In light of this, it is reasonable to assume that ER-WCA-MLP and EO-MLP are viable alternatives to the conventional methods. Also, the EO was more efficient in terms of complexity and, by extension, time-effectiveness, even if the ER-WCA had greater accuracy. Group models have been shown to have an R^2 value greater than 0.95 in the training set, while single models have an R^2 value of around 0.8 [33]. The very large increase in R^2 that happens after grid search improvement is a good sign that machine learning models are making accurate predictions. It's a good sign that this rise of about 15% is happening. Overall, the GS-XG Boost model did the best at generalization and making accurate predictions. It had R^2 values of over 99% in both the training and test sets. This made it possible for the model to be as accurate as possible. Because of what researchers and engineers have learned, they can now make better use of what they know to make and test things more quickly and accurately. A programme tool with an easy-to-use graphical user interface (GUI) makes this possible. The model was created utilizing raw materials and fresh mix parameters as predictors and strength properties as responses [34]. The results reveal that the application of admixtures improved the fresh and hardened characteristics of the concrete. Both geneticprogramming (GEP) and artificial neural networks (ANN) technologies GEP and ANN algorithms produced accurate predictions of the experimental data with minimum mistakes. However, GEP models may be favoured since the process generates simple equations, while ANN is merely a predictor. A neural network (ANN) investigates splitting tensile strength (Fs), compressive strength (Fc), elasticity modulus (Ec), and flexural strength [35]. ANN was trained and assessed using experimental programme data. Additions of CR, NS, FA, and P anticipated Fc, Fs, Ff, and Ec. ANN estimated strength accurately. The MoDs for Fc, Fs, Ff, and Ec were -0.28%, 0.14%, 0.87%, and 1.17%. Nearly none. The ANN model has an MSE of 6.45×10^{-2} and R^2 of 0.99496. Convergence analysis is performed throughout 100 simulations to conclude the model evaluation [36]. The training phase's greatest R^2 values were 0.9437, 3.9474, and 2.9074. In the testing stage, the highest values were 0.9285, 4.4266, and 3.2971, showing that ANN predicts compressive strength using BFS and FA well. The gold standard for artificial neural networks, with 24 neurons buried. Partial Influence Plots assess the ANN model's input variables' prediction effects. Sample age and cement content are the most critical factors in BFS and FA compressive strength. ANN algorithms save engineer's money on experimenting.

In order to forecast the performance of regular concrete, some scientists have created ANN models. So, although there are papers that discuss traditional ways of evaluating mechanical qualities, there doesn't seem to be many that look at SCC-WCS% using artificial neural network methodologies. The purpose of this research is to make a contribution to this field by suggesting an artificial neural network (ANN) formulation that can be used to forecast the reaction of self-compacting concrete with fly ash and waste copper slag in a rapid and accurate manner.

2. RESEARCH SIGNIFICANCE

The materials used to make SCC cause it to be more expensive than regular concrete (CC). Waste copper slag (WCS), an unwanted byproduct of more copper consumption, might one day replace fine aggregates in concrete structures. Despite numerous studies on applying ANN to SCC, a study that optimizes ANN efforts to predict the strength of SCC with fly ash and waste copper slag from different input layers of data in SCC mixes is needed. In the same manner, the data is used for training purposes to minimize computational effort in predicting the compressive strength of SCC-WCS%. The current study has the following objectives: To forecast the compressive strength, split tensile strength, and flexure strength of SCC-WCS% mixtures after 7, 28, 56, and 90 days of curing. The mechanical characteristics of SCC-WCS% blends are predicted using the Levenberg-Marquardt optimization ANN approach in MATLAB 2020a.

3. MATERIALS AND METHODOLOGY

3.1 Materials and proportions

Experimental evidence used for the purpose of forecasting the compressive strength of concrete. A reliable database on concrete compressive strength has been developed by taking into account nine variables: cementations, fly ash, fine aggregate, coarse aggregate, waste copper slag, water content, water-cementitious material ratio (W/C), superplasticizer and curing ages. For this investigation, the OPC 53 grade was specified by IS 12269-2015 [37]. In the Indian state of Andhra Pradesh, VTPS provided the fly ash (FA). For the study, collected aggregates from the surrounding region, ranging in size from 10 to 12.5 mm. Tap water was used as for testing and a 1.09 specific gravity HRWR is required to determine the SCC-WCS % combination characteristics according to evaluation of flow characteristics is mandated by EFNARC [38, 39], IS 10262: 2019 [40]. Eight distinct mixes were created, with one serving as a control mix. In SCC, the quantity of WCS utilised to replace natural sand can range from 0% to 70%. The required proportions for SCC mix are 425 kg/m^3 cement, 92.35 kg/m^3 flash, 904 kg/m^3 coarse-grain crushed aggregates, 740 kg/m^3 natural sand, 0.43 water to cement, 4.17 kg/m^3 PCE super plasticiser, and tap water. It takes around 8 to 10 minutes to get a uniform mixture using a pan mixer.

3.2 Methodology

3.2.1 Experimental program

In every single SCC combination, a total of 15 cube specimens measuring 100 mm × 100 mm × 100 mm, 15 cylinders measuring 100 mm × 200 mm, and 6 beams measuring 100 mm × 100 mm × 500 mm were precisely cast. Until the day of the test, the specimens were left to cure. After casting each mixture of SCC-WCS% for 7, 28, 56, and 90 days to cure, the cube compression test and split tensile strength were measured and recorded. The results of these tests were documented. The test results are considered as data set-I, consisting of 32 variations, for predicting the ANN-I model. Additionally, the test results for flexural strength after 28 and 90 days of curing are regarded as data set-II, including 16 variations, for predicting the ANN-II model using MATLAB 2020a.

3.2.2 Artificial neural networks (ANN) modelling

Using models of artificial neural networks (ANNs), researchers may probe the brain's encoding of abstract semantic information or visual images, even those with several levels of complexity. If this kind of "brain reading" and "mind-reading" works, it will be a huge step forward in the field of science. A neural network's biological neurons are its building blocks. Layers of tiny building blocks called neurons make them up. Each neuron in the hidden layer—the middle layer of a fully connected feed-forward artificial neural network—is connected to nodes in the layers that come before and after it.

Input nodes in the input layer receive data from the network, whereas neurons in the output layer are responsible for generating the network's output. A neuron's influence on another neuron is represented by the weights of the connections between their respective nodes. A neuron determines its output after receiving a signal from other linked neurons by adding up the weighted signals and using a function called. The Log-sigmoid function is used as activation by all of the network nodes [24-31].

The construction of an ANN model involves three primary steps:

- Defining the input and output for the problem.
- Training the network.
- Evaluating the network's performance by comparing actual and predicted values.

The present study utilizes two distinct data sets, as illustrated in Table 1 and Table 2, to predict the split tensile and compressive strengths. Data set 1 is employed for predicting split tensile strength outcomes, while data set 2 is utilized for forecasting flexural strength. The input variables in both data sets remain consistent across all training and testing phases. Two different methodologies are employed concerning the outcomes.

Table 1. Data set 1, in (Kg/cu.m)

Cement	Fly ash	CA	FA	WCS	Water	W/C	SP	Curing Days
425	92.35	904	740	0	182.75	0.43	4.17	7
425	92.35	904	666	74	182.75	0.43	4.17	7
425	92.35	904	592	148	182.75	0.43	4.17	7
425	92.35	904	518	222	182.75	0.43	4.17	7
425	92.35	904	444	296	182.75	0.43	4.17	7
425	92.35	904	370	370	182.75	0.43	4.17	7
425	92.35	904	296	444	182.75	0.43	4.17	7
425	92.35	904	222	518	182.75	0.43	4.17	7
425	92.35	904	740	0	182.75	0.43	4.17	28
425	92.35	904	666	74	182.75	0.43	4.17	28
425	92.35	904	592	148	182.75	0.43	4.17	28
425	92.35	904	518	222	182.75	0.43	4.17	28
425	92.35	904	444	296	182.75	0.43	4.17	28
425	92.35	904	370	370	182.75	0.43	4.17	28
425	92.35	904	296	444	182.75	0.43	4.17	28
425	92.35	904	222	518	182.75	0.43	4.17	28
425	92.35	904	740	0	182.75	0.43	4.17	56
425	92.35	904	666	74	182.75	0.43	4.17	56
425	92.35	904	592	148	182.75	0.43	4.17	56
425	92.35	904	518	222	182.75	0.43	4.17	56
425	92.35	904	444	296	182.75	0.43	4.17	56
425	92.35	904	370	370	182.75	0.43	4.17	56
425	92.35	904	296	444	182.75	0.43	4.17	56
425	92.35	904	222	518	182.75	0.43	4.17	56
425	92.35	904	740	0	182.75	0.43	4.17	90
425	92.35	904	666	74	182.75	0.43	4.17	90
425	92.35	904	592	148	182.75	0.43	4.17	90
425	92.35	904	518	222	182.75	0.43	4.17	90
425	92.35	904	444	296	182.75	0.43	4.17	90
425	92.35	904	370	370	182.75	0.43	4.17	90
425	92.35	904	296	444	182.75	0.43	4.17	90
425	92.35	904	222	518	182.75	0.43	4.17	90

Table 2. Data set 2 in (Kg/cu.m)

Cement	Fly ash	CA	FA	WCS	Water	W/C	SP	Curing Days
425	92.35	904	740	0	182.75	0.43	4.17	28
425	92.35	904	666	74	182.75	0.43	4.17	28
425	92.35	904	592	148	182.75	0.43	4.17	28
425	92.35	904	518	222	182.75	0.43	4.17	28
425	92.35	904	444	296	182.75	0.43	4.17	28
425	92.35	904	370	370	182.75	0.43	4.17	28
425	92.35	904	296	444	182.75	0.43	4.17	28
425	92.35	904	222	518	182.75	0.43	4.17	28
425	92.35	904	740	0	182.75	0.43	4.17	90
425	92.35	904	666	74	182.75	0.43	4.17	90
425	92.35	904	592	148	182.75	0.43	4.17	90
425	92.35	904	518	222	182.75	0.43	4.17	90
425	92.35	904	444	296	182.75	0.43	4.17	90
425	92.35	904	370	370	182.75	0.43	4.17	90
425	92.35	904	296	444	182.75	0.43	4.17	90
425	92.35	904	222	518	182.75	0.43	4.17	90

Initially, a multi-input, multi-output neural network, referred to as ANN-I, is utilized to predict all nine constituent inputs: cement, fly ash, coarse aggregate (CA), fine aggregate (FA), waste copper slag (WCS), water content, W/C ratio, superplasticizer (SP), and curing ages. The architecture of the ANN-I network is depicted in Figure 1, with only data set 1 applied to this network. The second approach considers curing times and employs a multi-input, single-output neural network named ANN-II to predict one ingredient at a time. The design of the ANN-II network can be seen in Figure 2.

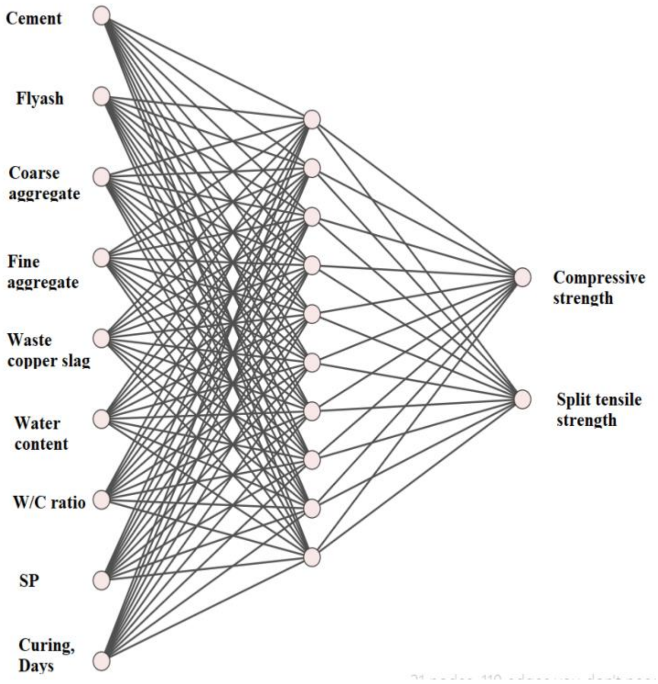

Figure 1. ANN-I network architecture in the present study

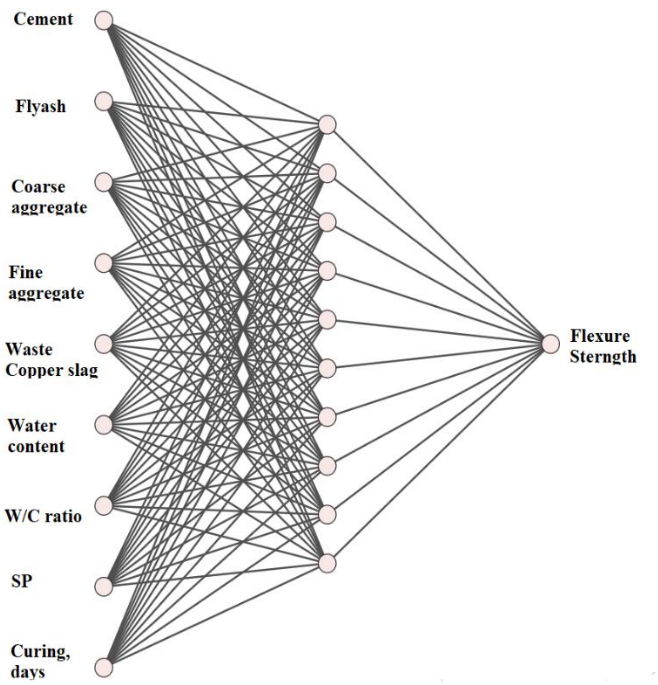

Figure 2. ANN-II network architecture in the present study

For the assessment of the compressive strength and split tensile strength prediction about 9 inputs with 10 hidden layer and 2 outputs at the different curing periods of 7 days, 28 days, 56 days and 90 days the compressive strength models and split tensile strength are tested in the laboratory it leads to 32 samples. For the assessment of the flexure strength prediction about 9 inputs with 10 hidden layer and 1 outputs at the different curing periods of 28 days and 90 days the flexure strength models are tested in the laboratory it leads to 16 samples. Both the ANN-I and ANN-II networks are trained and tested on all accessible datasets. The ideal number of 10 hidden layer nodes is calculated for both the ANN-I and ANN-II networks.

In general, the data set is separated into two parts: 80% for training and 20% for testing. The training may differ depending on the dataset, which is the bulk of the data set

you use to train the model. This involves updating the weights to optimise the ANN model matrix weights to determine the optimal map of input and output. Once the model has been trained, we freeze all of the weights before testing it on a new data set. In general, the model generates predictions, from which we measure the inaccuracy. Based on the mistake, we must train the data set by modifying the weights until the model has been trained. After training the model, all of the network weights are frozen and test the model It is critical to optimise data collecting for the artificial neural network. This study created a model with a 20% testing set for model testing, a 20% validation set for model validation, and a 60% training set for model training. During the learning phase, the Levenberg-Marquardt optimisation approach is used to train the ANN model, utilising the experimental data set as input. During the training phase, the weights and biases are modified to optimise the component prediction.

The Levenberg-Marquardt algorithm (LMA) is a local minimisation technique that relies on the least squares method. The Least Mean Absolute (LMA) technique is often used to optimise the weights and bias of multilayer perceptron (MLP) paradigms because it is very good at getting to the right values from very far away. Levenberg [41] and Marquardt [42] are the primary sources from which LMA is refined. The regularization parameter, also known as the Levenberg-Marquardt parameter, is used to stabilise Newton's approach; otherwise, the two methods are essentially similar. The convergence of each iteration automatically updates this parameter [43].

The MATLAB R2020a version is being used as the run-time environment. To evaluate the accuracy used in the research for assessing the learning, training, and predictive capacities of the constructed ANN model. The performance of the actual and projected values is compared using two methodologies: mean square error (MSE) and determination's coefficient (R^2). The results of this comparison are shown below:

$$MSE = \frac{1}{\mathrm{N}}\sum_{\mathrm{i=1}}^{\mathrm{N}}\sqrt{(\mathrm{Ai}-\mathrm{Pi})^2} \tag{1}$$

$$R^2 = 1 - \frac{\sum_{\mathrm{i=1}}^{\mathrm{N}}(\mathrm{An}-\mathrm{Pn})^2}{\sum_{\mathrm{i=1}}^{\mathrm{N}}(\mathrm{An}-\mathrm{Sn})^2} \tag{2}$$

When the R-squared value approaches 1, it suggests that the predictive models generated by ANN are well-suited for the provided datasets, indicating higher accuracy. Conversely, when the R-squared value approaches zero, it signifies lower accuracy or a poor fit for the data.

4. RESULTS AND DISCUSSION

The purpose of this research was to evaluate the viability of using ANN for the proportioning of SCC mixes. Two ANN models, ANN-I and ANN-II, are built using two distinct techniques. A data set is used to train and test each model. Two datasets, "data set 1" and "data set 2," compile experimental results from several studies [31-34]. During training and testing, all approaches and phases used inputs that were fixed in data sets 1 and 2. Utilizing the MATLAB (2020a) toolbox, an ANN model was created to forecast the mechanical characteristics of SCC.

4.1 ANN-I and ANN-II model: Data set 1 and data set 2 is used

In the ANN-I architecture, nine input variables are utilized along with 10 hidden neurons and 2 outputs, namely Compressive Strength and Split Tensile Strength, depicted in Figure 3. Furthermore, there is an additional output, Flexure Strength, represented in Figure 4. The correlation between experimental and predicted values is evaluated using the R-squared (R^2) value. The MATLAB (2020a) training function employs the Levenberg–Marquardt optimization technique for training the network, adjusting weight and bias values. The training state of the ANN-I model is illustrated in Figure 5a. An observation after epoch 4 indicates error repetition six times until tested at epoch 10, suggesting potential overfitting from epoch 5 onwards. Thus, epoch 4 is selected as the base, and its weights are finalized. Validation is conducted six times, with errors reported six times before the process concludes. Similarly, Figure 5b depicts the training state of the ANN-II model. Error repetition is noted after epoch 7, occurring three times until epoch 10, indicating overfitting beginning from epoch 6. Therefore, epoch 7 is chosen as the base, and its weights are finalized. Validation is carried out six times, with errors reported six times before the process stops. Figure 6a presents the validation and mean squared error performance of the network, transitioning from a large to a small value. Three lines represent different stages of training, validation, and testing. The best validation performance is achieved at epoch 4, with subsequent error repetition leading to termination at epoch 10. Employing a neural network with a hidden layer comprising 10 neurons aims to minimize Mean Squared Error (MSE) and maximize R, resulting in an R value of 0.99. Similarly, Figure 6b displays the validation and mean squared error performance of the network, with the best validation performance observed at epoch 7, resulting in an MSE of 0.41619. The process is halted at epoch 10 after error repetition occurs post-epoch 7, mirroring the previous model.

Figures 7a and 7b portray the error histograms of the ANN-I model, offering insights into the errors obtained during the training phase. These histograms suggest that errors across all three data groups are frequently close to the zero-error line, indicating relatively small numerical error values. Overall, the error histograms demonstrate that the training phase of the constructed ANN model is completed with minimal errors. To validate the trained neural network, a dataset containing strength, and flexure strength, as discussed earlier, was assembled.

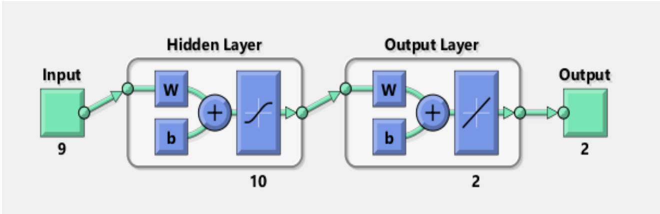

Figure 3. Structure of the developed ANN-I

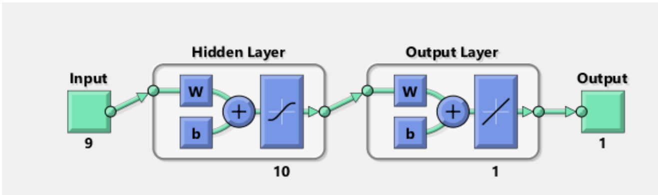

Figure 4. Structure of the developed ANN-II

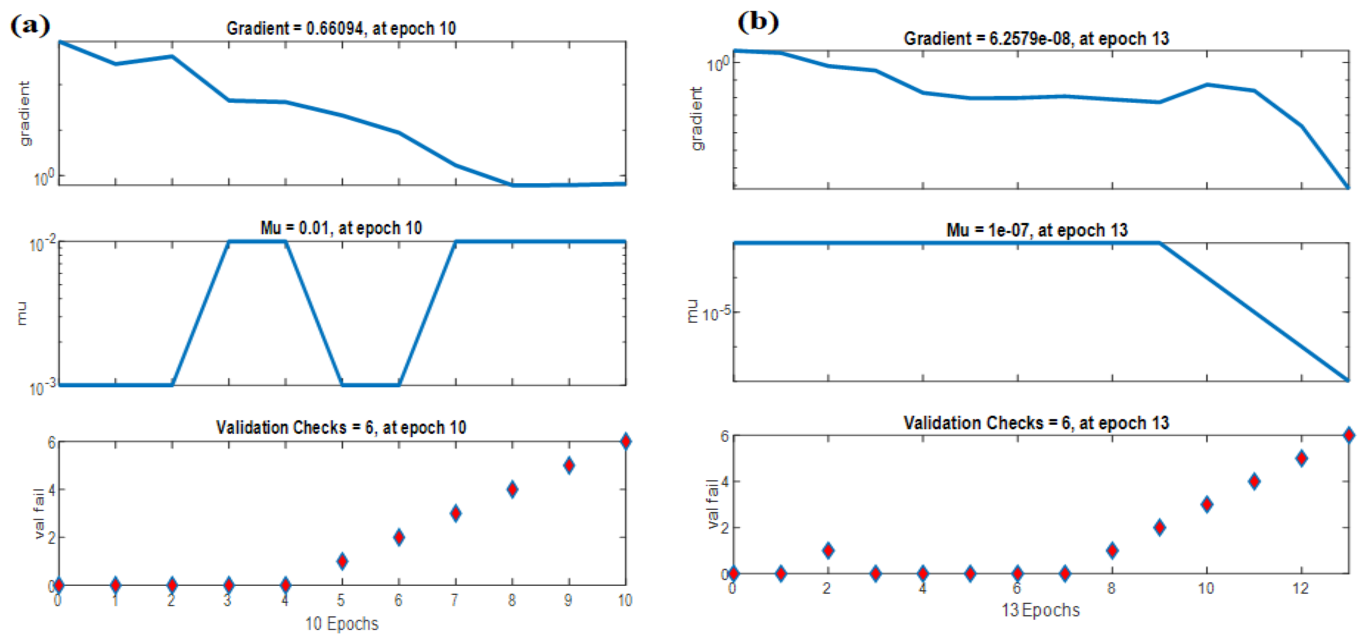

Figure 5. Training state: (a) ANN–I model; (b) ANN–II model

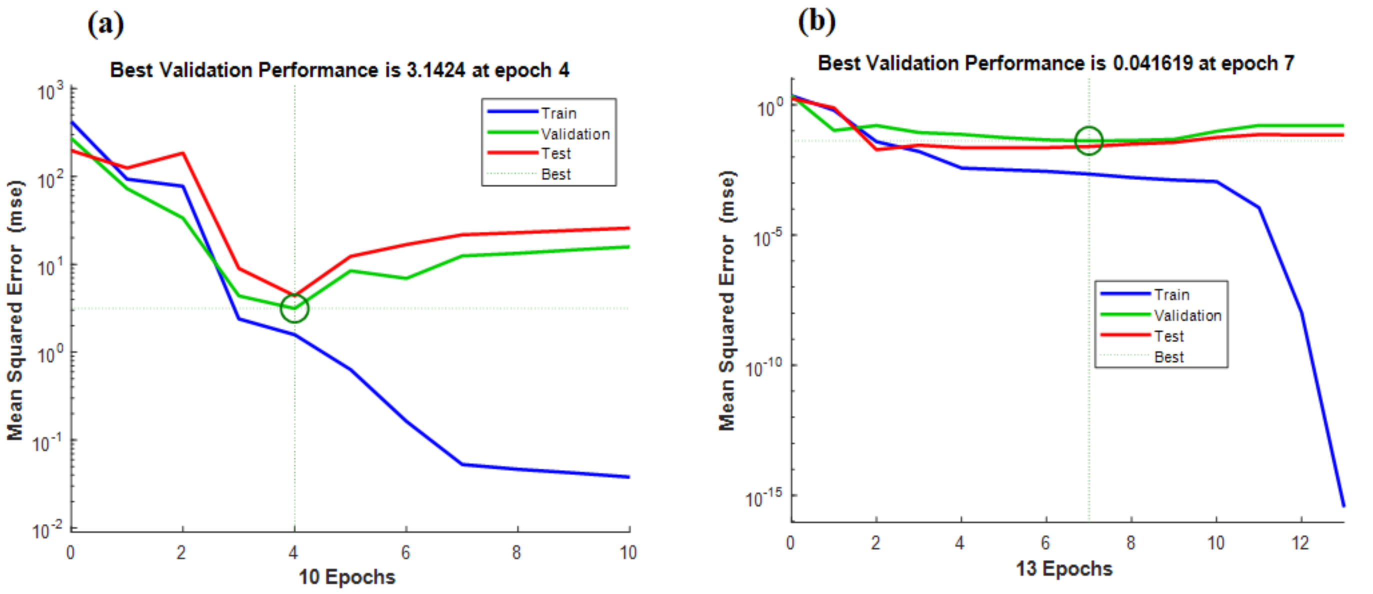

Figure 6. Performance network: (a) ANN –I model; (b) ANN –II model

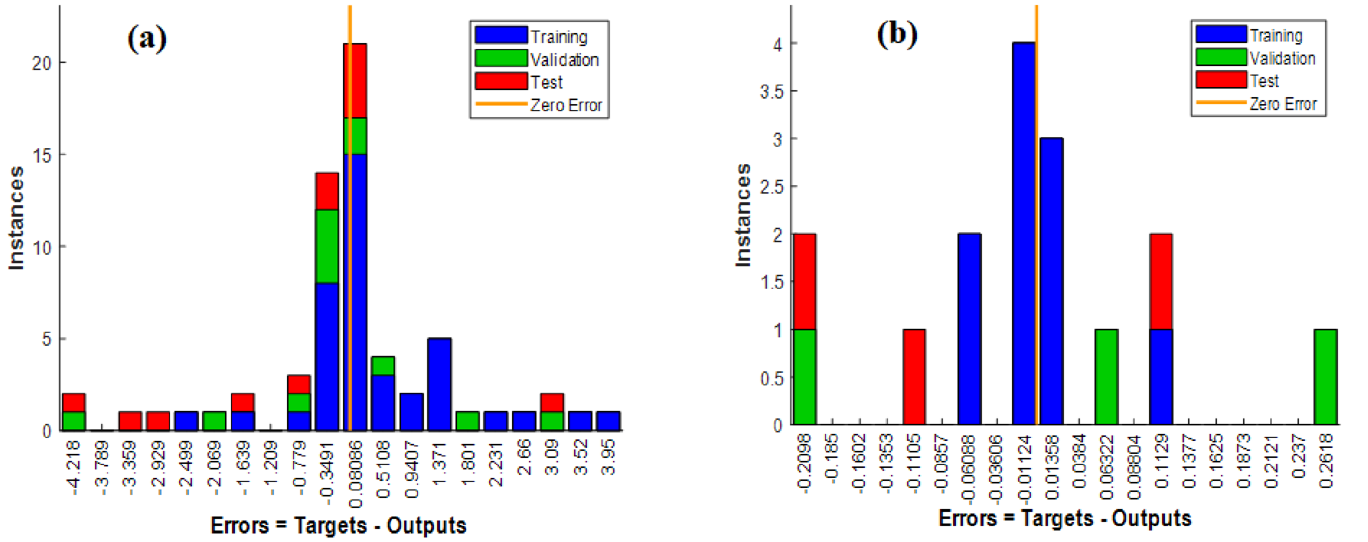

Figure 7. Error histogram: (a) ANN –I model; (b) ANN –II model

Regression plots for validation, testing, and training of ANN-I and ANN-II models are depicted in Figures 8 and 9, respectively. These plots illustrate the compatibility between experimental and predicted outcomes. The error relative to the expected value falls within the range of 0.025 to 0.105. Figure 10a shows the experimental and predicted values of compressive strength for the ANN-I model. For the assessment of the compressive strength and split tensile strength prediction about 9 inputs with 10 hidden layer and 2 outputs at the different curing periods of 7days, 28 days, 56 days and 90 days the compressive strength models and split tensile strength are tested in the laboratory it leads to 32 samples. Table 1 represents the data set 1 for the assessment of ANN-I model, based on that the predication is carried in MATLAB. The figure 10a represents strong correlation between the experimental compressive strength data at different curing periods to the train model. The coefficient correlation of an R^2 value of 0.975 and an error of 0.025. Figure 10b displays the experimental and predicted values of split tensile strength for the ANN-I model. In the Figure 10b represents strong correlation between the experimental split tensile data at different curing periods to the train model. The coefficient correlation of an R^2 value of 0.96 and an error of 0.04.

Figure 11 presents the experimental and predicted values of flexure strength using the ANN-II model. For the assessment of the flexure strength prediction about 9 inputs with 10 hidden layer and 1 outputs at the different curing periods of 28 days and 90 days the flexure strength models are tested in the laboratory it leads to 16 samples. Table 2 represents the data set 2 for the assessment of ANN-II model, based on that the predication is carried in MATLAB. Figure 11 represents good correlation between the experimental flexure strength data at different curing periods to the train model. The coefficient correlation of an R^2 value of 0.895 and an error of 0.105. The Mean Squared Error (MSE) values for the ANN-I and ANN-II models are calculated to be 3.8905×10^{-2} and 2.525×10^{-2}, respectively. Additionally, the R^2 values for the ANN-I and ANN-II models are determined to be 0.985 and 0.9983, respectively.

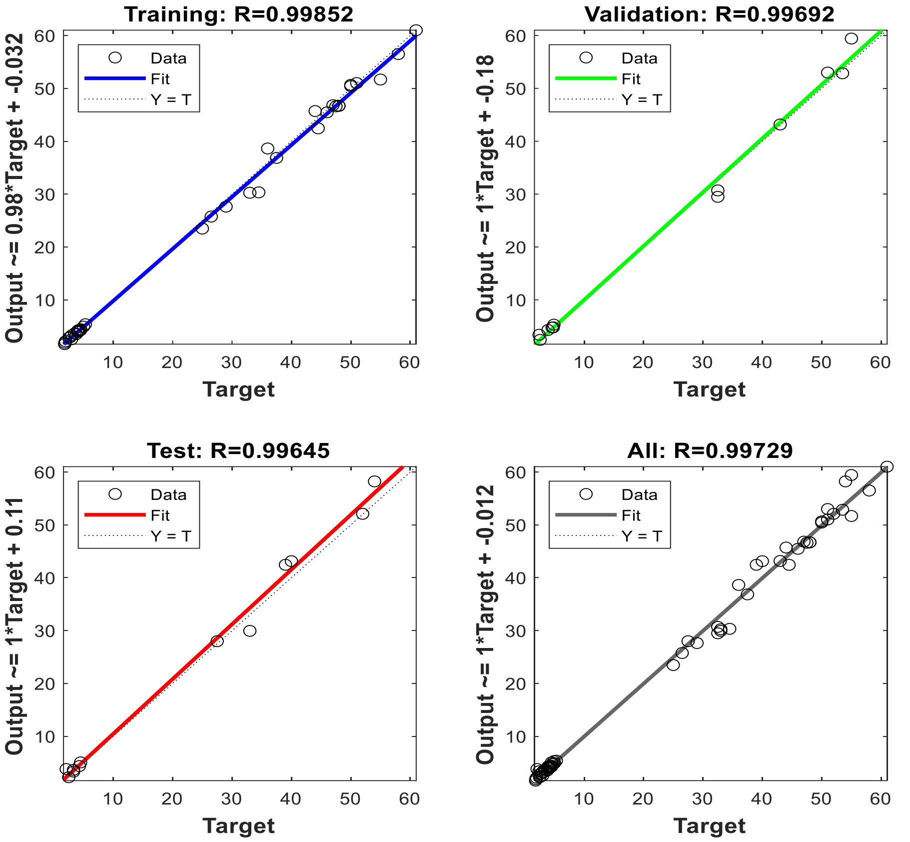

Figure 8. Regression network ANN-I model

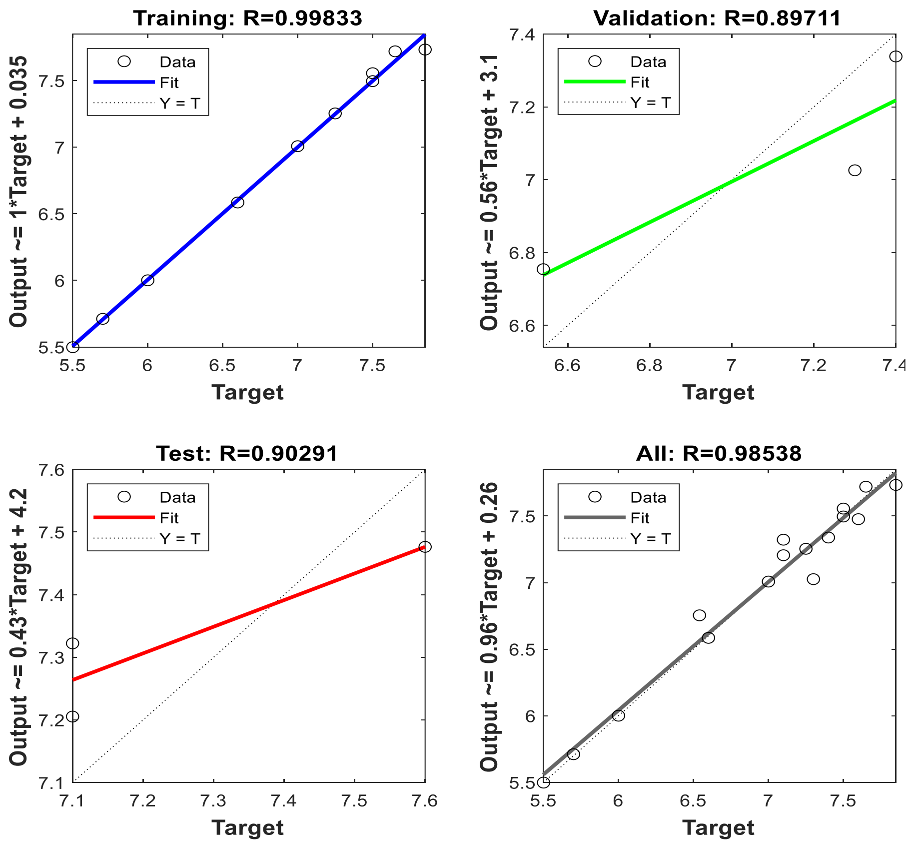

Figure 9. Regression network ANN-II model

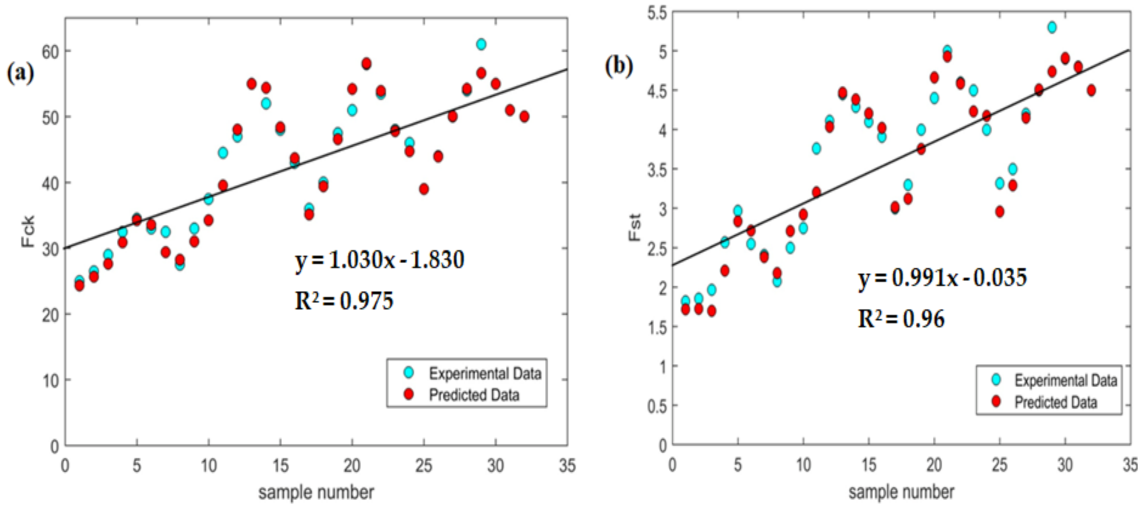

Figure 10. Experimental vs Predicated values of ANN-I model: (a) Compressive strength (MPa); (b)Split tensile strength (MPa)

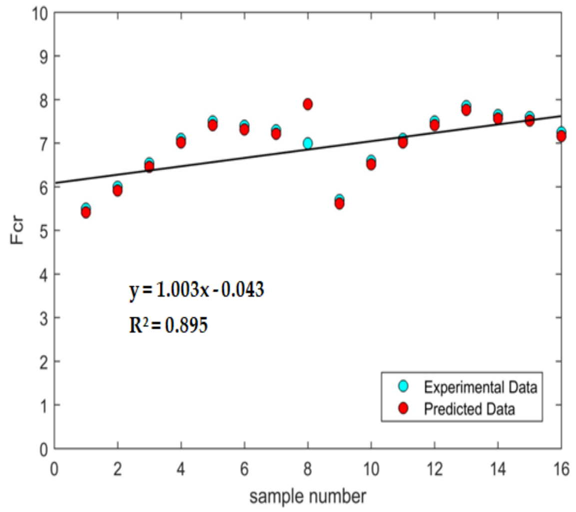

Figure 11. Experimental vs Predicated values of ANN-II model of Flexure strength (MPa)

5. CONCLUSIONS

The paper presents an attempt to use ANN for SCC-WCS% mixes. The artificial neural network (ANN) algorithm utilizing nine independent input factors with two datasets showed a more dependable and accurate prediction capacity for mechanical characteristics. The results of the experiments for the datasets of various curing ages, the trained neural networks may be used to execute mix proportioning of SCC mixes with waste copper slag and fly ash which are used in the simulation led to these conclusions.

- The ANN-I model exhibited regression values of 0.99852, 0.99645, and 0.9962 for training, testing, and validation, respectively. Conversely, for ANN-II, the regression values stood at 0.99833, 0.90291, and 0.8971 for training, testing, and validation, respectively.
- Optimal validation performance is achieved at epochs 4 and 7 for the ANN-I and ANN-II models, respectively. These models demonstrate accurate predictions for the compressive strength, split tensile strength, and flexural strength of SCC.
- Experimental data from this study were utilized to validate the ANN models by comparing predicted and experimental results of SCC. The analysis revealed satisfactory relationships between predicted and experimental values of compressive strength of SCC-WCS%, with respective R^2 values of 0.975, 0.960, and 0.895, alongside errors ranging from 0.025 to 0.105. The correlation of the experimental data to the predicted ANN model shows better relation with the self compacting concrete incorporating the fly ash as cement and fine aggregate as waste copper slag at the different curing period.
- The Mean Squared Error (MSE) values for the ANN-I and ANN-II models are 3.8905×10^{-2} and 2.525×10^{-2}, respectively, while the corresponding R^2 values are 0.985 and 0.9983.

The ANN models allow for the reliable prediction of mechanical properties of SCC-WCS%, which consequently influence complex processes. The future work in SCC mixes is to assess the large data finding based approaches at the different mix proportion at different curing ages is important. Consequently, it is suggested to record and forecast collective SCC behaviors taking these elements into account.

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