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Predictive Models for Evaluation of Compressive and Split Tensile Strengths of Recycled Aggregate Concrete Containing Lathe Waste Steel Fiber

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ABSTRACT

The increasing demand and growing pressure on natural aggregates necessitated recycling and reusing recycled concrete aggregate (RCA). The proper implementation of RCA for concrete production lags, possibly because there is currently no adequate stand-alone data to predict its quality. Consequently, many tons of RCA are accumulated as landfills and are a threat to the public. In an attempt to stop the recurrence of experimental studies and the wasting of scarce resources, the present study proposed statistical models for the evaluation of the compressive and split tensile strengths of the recycled aggregate concrete (RAC) comprising Lathe Waste Steel Fibre (LWSF), utilizing the Artificial Neural Network (ANN). Crushed granite (CG) was partially replaced with RCA from 0% to 100% in increments of 25% and LWSF as reinforcement at a constant amount of 1.5% by volume fraction. The fresh and hardened concrete's properties, such as workability, compressive and splitting tensile strengths, were studied. The results showed that 25% RCA with 1.5% LWSF (RACS1) increased the compressive strength and workability, while the split tensile strength reduced substantially. The ANN model was developed based on six input variables; namely: ordinary Portland cement (OPC), river sand (RS), CG, RCA, water-cement ratio (WC) and concrete age (CA), whereas the compressive and split tensile strengths were the response variables. The input data was learned, verified and validated using the feed-forward back-proportion approach for ANN. The most probable model architecture, comprising a six-input layer, twelve-hidden layer and two-output layer neurons, was selected based on acceptable results in terms of mean square error, MSE, after several trials. As a result, the selected ANN model was found to be capable of reproducing experimental results.

KEYWORDS: Recycled aggregate concrete (RCA), Lathe waste steel fiber (LWSF), Compressive strength, Splitting tensile strength, Artificial neural network.

INTRODUCTION

For decades, concrete has become the primary construction material used in structural infrastructure projects, such as buildings and storage facilities. Its essential constituents are cement, sand and granite, coupled together with water. About 60% of the composition is assumed to be the amount of the coarse aggregate. Consequently, rising prices, environmental effects, energy demand, growing production, diminishing supplies and increasing pressure on natural resources have necessitated recycling and reuse of waste, such as recycled concrete aggregate (RCA), through efficient building practices (Afolayan and Alabi, 2013).

The primary source of RCA, as accounted for by Ramadevi et al. (2017), Hunashikatti et al. (2018) and Alabi and Mahachi (2020), is from the renovation and demolition debris (R&D) and laboratory-tested samples (LTSs). Hence, this tends to be the most affordable and safe alternative to increasing demand for natural resources and the landfill (Choi, 2017; Sancheti et al., 2020). However, various studies on possible utilization of RCA as a partial or complete substitution for natural aggregates (NAs) in the RAC have been carried out (Verian et al., 2018; Ahmed et al., 2020).

This type of concrete has been found not to fulfill the minimum strength criteria (Behera et al., 2014; Ahmed et al., 2020; Cantero et al., 2020), workability

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specifications (Verian et al., 2018; Kazmi et al., 2020) and durability criteria as opposed to traditional concrete (TC), as it has experienced some processing (Zhu et al., 2019; Zhu et al., 2020). Also, RAC produced with RCA has also been found to be weak in tension and adversely affected by many other variables, such as higher replacement fraction of RCA (Malešev et al., 2010; Behera et al., 2014), origin, physio-mechanical properties (Gomes et al., 2015), size, susceptibility status of initial concrete (De et al., 2016), amount of mortar attached and aggregate surface texture (Butler et al., 2014).

However, numerous types of fiber, such as carbon (Tanyildizi, 2018), cellulose (Ma et al., 2020), basalt (Li et al., 2020), bagasse and hemp (Ruano et al., 2020), aramids and steel (Kalpana and Tayu, 2020), have been introduced in an attempt to improve the properties of RAC. Lathe waste steel fiber (LWSF) is used in this study to enhance the concrete properties when mixed into the concrete. Hence, this is available in abundance at the University's Mechanical Engineering Laboratory. Vytlacilová (2011) and Fang-Yuan et al. (2018) observed a significant change in RAC's mechanical properties with plastic fibers' inclusion. Fibers structured in the direction of tensile stress were found to improve direct tensile strength by up to 133% with the inclusion of 5% of straight steel fibers (Nguyen, 2013).

To avoid duplicating experiments and wasting scarce resources, based on previous studies, simple models using the best-fit regression curve have emerged capable of reproducing concrete properties (Shafabakhsh et al., 2015; Imam et al., 2018). Apparently, because of the non-linear nature of concrete and the uncertainty involved with its production, this approach cannot accurately forecast the concrete's exact nature. Interestingly, the implementation of Artificial Neural Networks (ANNs) have been found capable of modeling any designated material properties based on the specified input parameters. Also, ANN has gained more popularity in modeling concrete properties and has shown some exciting results (Abdalla and Hawileh, 2011; Deshpande et al., 2013; Imam et al., 2015; Imam and Kazmi, 2017). Therefore, this study focuses on the ANN technique's performance to model and estimate compressive strength, f_{cu} and split tensile strength, f_{SL} of RAC containing LWSF.

Experimental Setup

Materials

The aggregates used in this study included well-formed river sand (RS) as a fine aggregate, crushed granite (CG) and crushed concrete cubes as a recycled coarse aggregate (RCA) obtained from the Structural Engineering Laboratory. The maximum grain size of the RS used was 4.75 mm. The fineness modulus, the absolute (specific) gravity and the saturated surface dry (SSD) water absorption of RS are 3.0, 2.49 and 2.56%. Crushed granite (CG) with a maximum of 20 mm diameter was used as a coarse aggregate in concrete. RCA with differing sizes between 20 mm and 10 mm, as seen in Figure 1, produced from concrete cube debris in the Structural Laboratory, was used as a partial replacement for CG. Lathe waste steel fiber (LWSF), as seen in Figure 2, used in this study, is a by-product of machined high-yield steel on a lathe machine. LWSF is a circular structure with a diameter of 0.29 mm and a length between 25 mm and 38 mm. The cement used was 3X ordinary Portland cement (OPC) grade 42.5R conforming to BS 12 (1995). Portable water conforming to ASTM 1602 (2012), clear of any constituent capable of impacting the concrete properties, was used to mix and cure the concrete.

Figure (1): RCA (laboratory-tested samples)

Figure (2): Lathe waste steel fiber

Method

A concrete mix ratio of 1:2:4 by wt. of cement, sand and granite was adopted with a water-cement ratio of 0.45. The cement and RS proportions were kept constant at 100%. The details of the design of the concrete mix are given in Table 1. Five (5) different concrete mixtures have been prepared; one traditional concrete (TC), which serves as a control mix made of 100% CG without LWSF and four (4) other concrete mixes with 25% to 100% in steps of 25% containing a steady 1.5% inclusion of LWSF (RCAS1 to RCAS4). The workability of fresh concrete samples was determined using the slump test method, as suggested by BS 12350-2 (2009). The hardened samples, after being de-molded and stored underwater for 7 days and 28 days, were examined for compressive strength in compliance with BS 12350-3 (2009). The splitting tensile strength test was also conducted on cylinder samples at 7 days and 28 days, in compliance with the standard research procedure in BS 12390-3 (2009). The mean value of the three specimens was reported. The results obtained were further analyzed to make inferences on the effect of the RCA substitution level on the concrete's strength characteristics.

Table 1. The five different mix designs used for concrete production

Notation	Concrete mix design
Control	Control mix using 100% CG in the concrete
RACS1	25% replacement of CG with RCA with constant LWSF content of 1.5%
RACS2	50% replacement of CG with RCA with constant LWSF content of 1.5%
RACS3	75% replacement of CG with RCA with constant LWSF content of 1.5%
RACS4	100% replacement of CG with RCA with constant LWSF content of 1.5%

Artificial Neural Network Architecture

The Multilayer Perception Levenberg-Marquardt (MLP) concept with a feed-forward back-proportion paradigm was implemented because of its flexibility to solve multi-dimensional or unidentifiable problems due to its overall network architecture (Shabani and Norouzi, 2015). The MLP introduces the training dataset to the Artificial Neural Network (ANN) and modifies the weights to eliminate or minimize the prediction error between the observed and the predicted outputs. In other terms, the result of a neuron is the weighted total of the inputs plus the bias, b enabled by the transfer function, $f(\varphi)$ as in Equation (1).

$$O = f(\varphi) = f\left(\sum_{i=1}^{n} w_i x_i + b\right) \tag{1}$$

where O is the predicted (response) values, $x_1, x_2, \ldots, x_n$ are the inputs, w_i is the weight vector. The variable φ is defined as a scalar product of the weight and input vectors.

In this research paper, 70% of the input data was used for training to create an ANN model for predicting compressive strength, f_{cu} and split tensile strength, f_{SL} using the MATLAB® framework. The six input variables used for neural network training are: OPC, RS, CG, RCA, water-cement ratio (WC) and concrete age (CA). In other words, there are six neurons in the input layer. The outputs are f_{cu} and f_{SL}; therefore, the output/prediction layer has two neurons. Since there is no unique approach to define the number of neurons in each hidden layer, many trials were conducted before selecting the most probable number of hidden layers and neurons. The selected layers and neurons were found to meet the Mean Square Error, MSE and multiple coefficients of determination (R^2) criterion as described in Equations (2) and (3) (Larbi et al., 2019; Abdalla and Hawileh, 2011; Deshpande et al., 2013; Garzón-roca et al., 2013). After that, the network was established. In other words, after the completion of the training phase, the structure was provided with test data to validate and assess the credibility of the trained system. In this study, the difference between the observed and the predicted (output) values is considered a prediction error.

$$MSE = \frac{1}{N_d}\sum_{i=1}^{n}\left(\hat{O}_i - O_i\right)^2 \tag{2}$$

$$R^2 = 1 - \frac{\sum\left(\hat{O} - O\right)^2}{\sum\left(\hat{O} - \bar{O}\right)^2} \tag{3}$$

where $\hat{O}$ is the observed value, O is the predicted value of $\hat{O}$ and $\overline{O}$ is the mean value of the $\hat{O}$ costs. N_d is the total number of data.

RESULTS AND DISCUSSION

Concrete Workability

After thoroughly mixing the concrete, the slump cone was used to test the fresh concrete's workability. Figure 3 displays the effects of the slump test on various concrete mixtures. The height of the slump ranged from 40 mm to 60 mm. Slump values are found to decrease as the amount of RCA substitution with CG rises. Hence, this may be related to the assumption that mixing water rises due to higher porosity, the amount of mortar adhered to RCA and RCA's absorbing potential. It was observed that RACS1 had attained the same slump value as the control sample. However, with the inclusion of LWSF, the slump value of other mixtures decreases as the RCA substitution level increases. Therefore, this may be attributed to a high degree of water absorption, leading to a comparatively high degree of mortar adhesion.

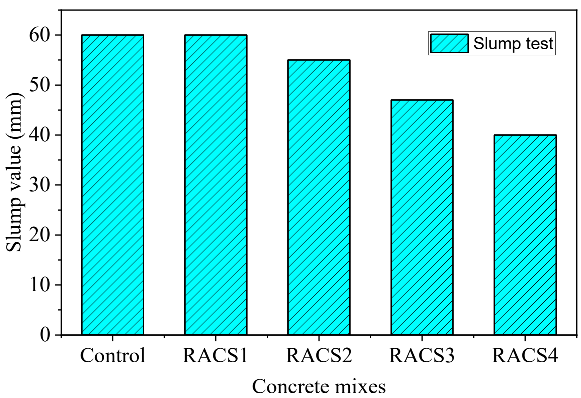


Figure (3): Results of slump test for different mixes

Compressive Strength

Figure 4 indicates the compressive strength at 7 days and 28 days for all mixtures (i.e., control and RACS) prepared from RCA and CG. The compressive strength change of control samples between 7 days and 28 days was slower and the compressive strength at 7 days surpassed the predicted strength at 28 days. The disparity in intensity between 7 days and 28 days for both concrete mixtures was found to be 74.4%, 16.66%, 163.75%, 133.87% and 156.21%, respectively. From Figure 4, it can be seen that the RACS is distinguished by a lower compressive strength relative to the control sample. In other terms, the drop in compressive intensity was defined as the RAC's level substitution rises from 0% to 100%. The low compressive strength found can be due to the origin and experience of the RCA. The adhesion of the old mortar to the RCA aggregates may have led to the decreased intensity reported. As the % substitution rose from 25% to 50%, a substantial decrease of 20.28% to 67.35% in compressive strength at 7 days was observed. However, a small reduction in compressive strength at 28 days was observed. The decline in compressive strength for the 75% CG substitution was 63.12% at 7 days and 50.60% at 28 days. When CG was substituted with 100% RCA, the compressive strength decrease was 71.32% and 57.92% at 7 days and 28-days, respectively. The aggregate form and surface hardness were visually observed to have contributed to lower concrete's strength properties.

However, most of the noticeable reduction in compressive strength was at 7 days. Hence, this may be due to the variation in the RAC's physio-mechanical properties used in making concrete, sourced from different original concretes with different strengths. However, the compressive strength was improved at 25% and 50% RCA replacement levels with 1.5% LWSF (RACS1 and RACS2). In other words, when the RCA replacement level was between 25% and 50%, the compressive strength was observed to be higher compared with the control samples, after which the compressive strength obtained decreases. This finding was found to agree with the study of Waigh et al. (2013).

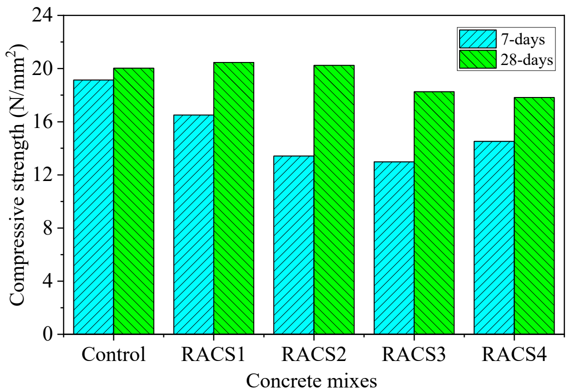


Figure (4): Compressive strength at 7 days and 28 days for different concrete mixes

Splitting Tensile Strength

Figure 5 displays the splitting tensile strength of control samples with the RACS at 7 days and 28 days. A declining pattern in splitting tensile strength was noticed from the formation when the percentage substitution of CG with RCA was raised. At 7 days and 28 days, the concrete mix with 100% RCA and 1.5%LWSF (RACS4) had the lowest tensile strength of 1.5 N/mm^2 and 2.4 N/mm^2. The reduction in split tensile strength of the RACS was found to vary from 10.7% to 46.4% compared to the control samples. Higher reductions may be due to the fiber's orientation impact on the interfacial zone between new and old mortar paste adhering to the RCA. However, this could also be attributed to weak bonding between the fiber and RCA (Ghorbani et al., 2019; Sasanipour and Aslani, 2020).

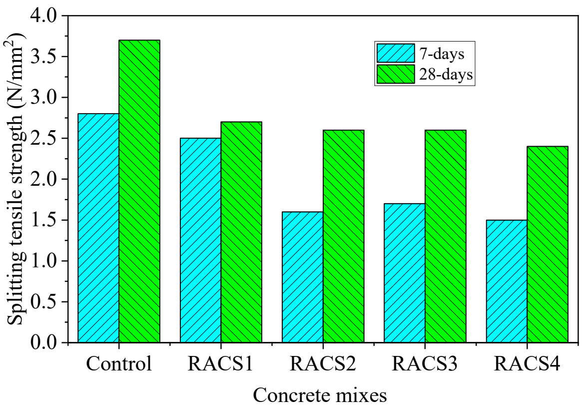


Figure (5): Splitting tensile strength at 7 days and 28 days for all the mixes

Artificial Neural Network (ANN)

The most probable ANN architecture that produced the best outcome after several network training trials comprises one hidden layer with twelve neurons and two output layers (i.e., 6-12-2), with the lowest MSE value, as shown in Figure 6. Figures 7 and 8 also display matching the observed data values and the predicted data values, with their corresponding error values, utilizing f_{cu} and f_{SL} datasets. The matches are generally acceptable. It was also found that there is a good statistical correlation between the predicted data and the measured data, which may be attributed to an insignificant difference between the two data types. In other words, the chosen most probable ANN prediction model was very similar to the observed data and the phase shift was marginal. The estimates found that the corresponding percentage relative error for both the predicted f_{cu} and f_{SL} is marginal and reflects a valid prediction model. Therefore, it could be inferred that the proposed ANN model class effectively predicts f_{cu} and f_{SL} based on the set of test data.

Also, to assess the proposed ANN model's performance and its ability to generalize prediction beyond training data, a new set of data was provided to the model. Figure 9 shows the correlation between the estimated f_{cu} and f_{SL} values and the concrete samples' measured f_{cu} and f_{SL} values for training and testing. Figure 9 further confirms the existence of a high correlation between the measured and the predicted values. Table 2 presents an estimate of the quality of the ANN model. For the test data, the values obtained for R^2 and MSE are 0.9898 and 0.0235, suggesting a reasonable accuracy. Based on the calculated value of R^2 alone, this means that about 99% variance in f_{cu} and f_{SL} is described by the six (6) input variables with a minimized error, thus validating the model. Hence, this can also mean that the chosen ANN model can forecast the measured data outcomes at a confidence level of 99%.

The normality test carried out on the f_{cu} shows that the p-value is greater than 0.05 (i.e., p-value > 0.05). Hence, this suggests that there is no significant deviation from a normal distribution. Table 3 shows the results of a two-way univariate analysis of variance (AVONA). It is observed that the p-value for the influence of % substitution on the compressive strength is less than 0.05 (p-value = 0.002 < 0.05) with a significant partial η^2 of 34.4%. The p-value for days (curing age) is also less than 0.05 (p-value = 0.000 < 0.05) with a significant partial η^2 of 47%. However, this suggests that there is a statistically significant difference. Indeed, from Table 3, the p-value for the relationship between the % replacement and the days is greater than 0.05 (p-value = 0.147 > 0.05) with a significant partial η^2 of 31.7%. Hence, this means that there is a statistically insignificant interaction effect between the variables. It was further observed that the effect of % replacement, days and the relationship between variables explains only about 34.4%, 47% and 31.7% of the total variability in compressive strength. It may be inferred that the curing period's effect on the compressive strength is more significant than the influence of the % substitution.

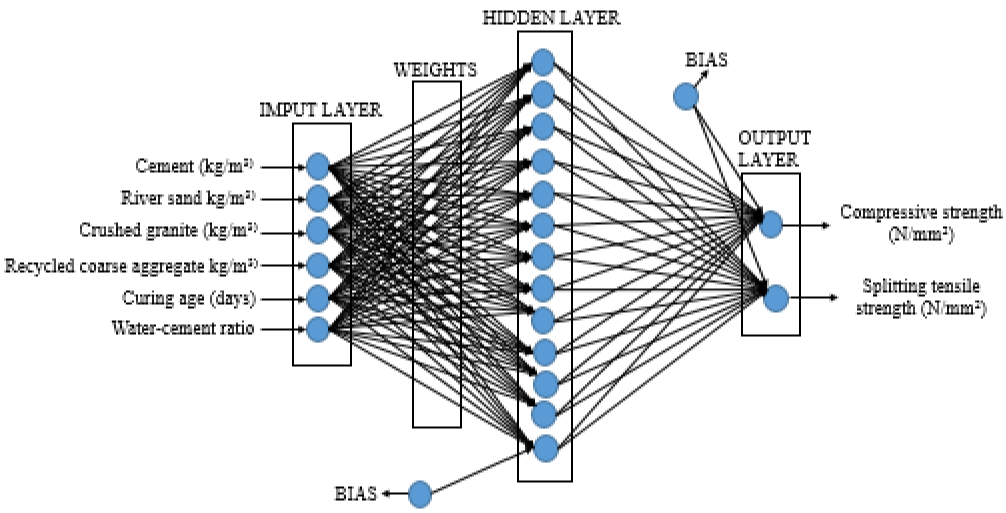


Figure (6): Most probable ANN architecture for compressive and splitting tensile strength, N/mm² prediction

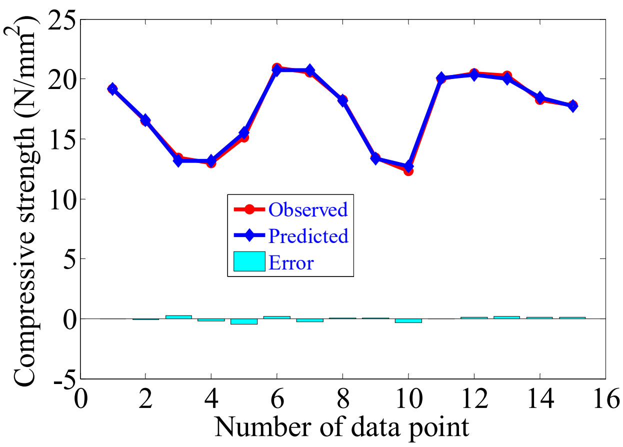


Figure (7): Matching between observed and predicted values of f_{cu} for all data

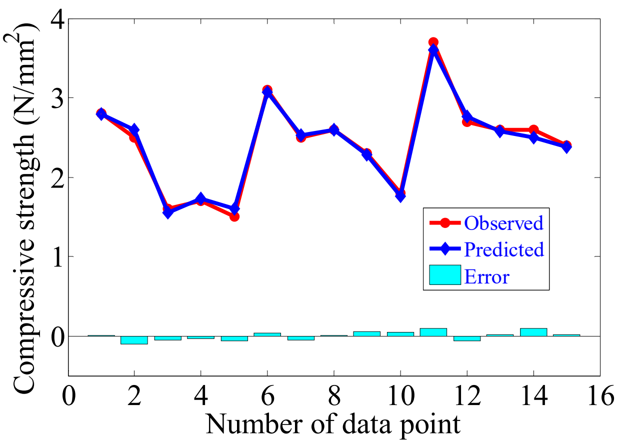
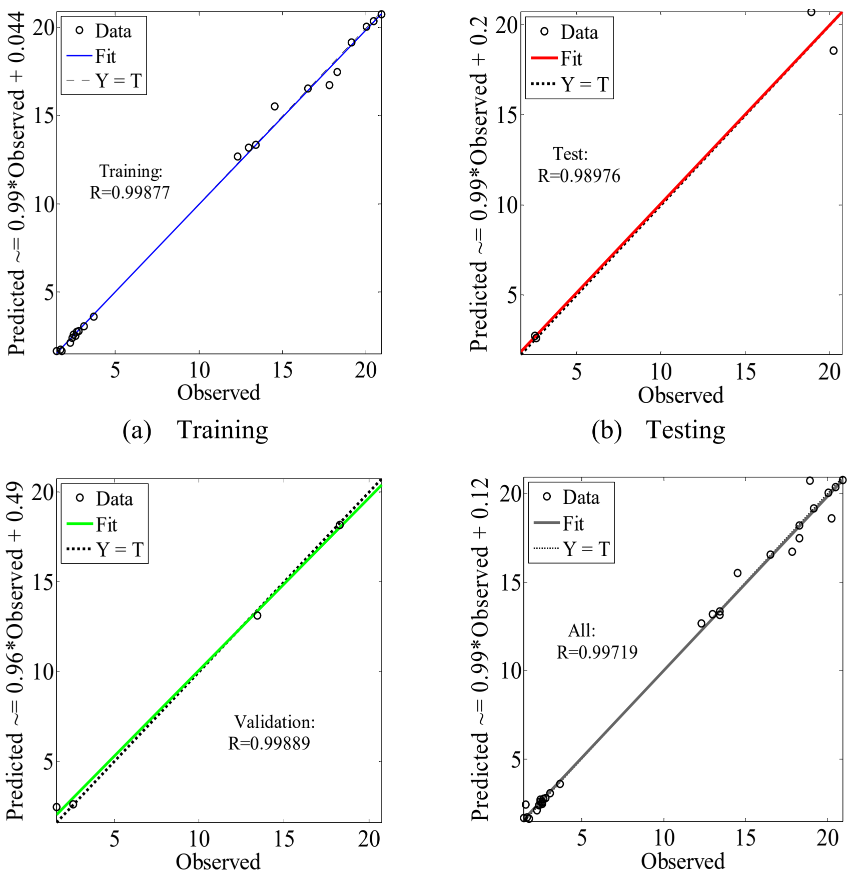


Figure (8): Matching between observed and predicted values of f_{SL} for all data



(a) Training (b) Testing

(c) Validation (d) All data set

Figure (9): Correlation between the observed and predicted data

Table 2. Performance indices for optimum ANN model

ANN	Training		Testing		Validation	
	R^2	MSE	R^2	MSE	R^2	MSE
Training	0.9988	0.4055	0.9898	0.0235	0.9989	0.0040

Table 3. Summary of two-way univariate ANOVA results

Property	Effect	df	Mean square	*F*-value	*p*-value	Partial η^2
Compressive strength	% replacement	4	45.11	5.25	0.002	0.344
	Days	3	101.68	11.83	0.000	0.470
	Interaction between % replacement and days	12	13.32	1.55	0.147	0.317

Concluding Remarks

This study provides a report on RCA usage from laboratory-tested samples containing LWSF as reinforcement in concrete. It was reported that the values of split tensile strength and workability are reduced by increasing the percentage of RCA. In the meantime, compressive strength at 25% and 50% RCA with 1.5% LWSF content was found to perform better than the TC. As the percentage rises past 50%, compressive strength and workability slowly reduced. The inclusion of LWSF was found to have a small noticeable impact on compressive and split tensile strengths owing to weak interfacial zone bonding between new and old mortars connected to the aggregates. To obtain an acceptable prediction of f_{cu} and f_{SL} of RAC containing LWSF within a short time, this study further describes ANN's effectiveness in reproducing and predicting f_{cu} and f_{SL}, using the laboratory dataset. Various significant factors, such as OPC, RS, CG, RCA, WC and CA, were used as inputs in the developed models' ANN back-propagation training process. Both the measured and the predicted f_{cu} and f_{SL} values were contrasted using the parameters MSE and R^2. It was reported that the established ANN model would significantly predict the observed f_{cu} and f_{SL} values with marginal discrepancies. Besides, this means a good match between the ANN forecast model and the measured data. Finally, the proposed ANN approach provides a powerful tool to study the estimation of f_{cu} and f_{SL} of concrete in a general situation.

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