MODELING THE TENSILE STRENGTH OF CONCRETE WITH POLYETHYLENE TEREPHTHALATE (PET) WASTE AS REPLACEMENT FOR FINE AGGREGATE USING ARTIFICIAL NEURAL NETWORK

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Abstract: Tensile strength of concrete made with polyethylene terephthalate (PET) waste as replacement for fine aggregate was modelled using artificial neural network. A multilayer feedforward neural network (MLFFNN) and radial basis function (RBF) methodology were compared to see which was more accurate. The MLFFNN modelling results showed a predictive accuracy of 95.364% and a root mean square error value of 4.4409×10^{-16} while RBF neural network modeling results showed a higher predictive accuracy (99.509%) with a lower root mean square error value (1.6653×10^{-16}). It is concluded that ANN models accurately predicted the tensile strength of PET concrete.

Keywords: artificial neural network, concrete, fine aggregate, polyethylene terephthalate, tensile strength

1. INTRODUCTION

About 25 billion tons of concrete are produced annually around the world [1]. In 2018 there were around 4.1 and 48.3 billion tons of aggregate and cement use, respectively [2]. Overconsumption of raw materials may lead to the release of greenhouse gases, which may accelerate global warming. Therefore, researchers have concentrated on producing sustainable materials for concrete manufacturing from wastes to decrease the impact of concrete construction on the environment.

200 billion pounds of fresh plastic material are foamed annually throughout the world, and more than 100 million tons of plastics are produced each year. Additionally, more than one million plastic bottles and five trillion plastic bags are bought every minute, respectively [3]. After use, people threw plastics in open spaces and water because they were unaware of the harmful consequences of plastics. As a result, in terms of environmental pollution, plastic trash came in third after food waste and paper waste. Plastic wastes have a complex behavior since they are durable and require a long time to breakdown [4].

New techniques for disposing of plastic garbage are required [5]. The best way to save money, lessen pollution, and improve the unexpected qualities of concrete is to use this rubbish as aggregate material [6]. Numerous studies have revealed that the characteristics of concrete were dramatically impacted by the usage of plastic trash. The engineering characteristics of PET fiber reinforced concrete [7, 8], the impact of crushed plastics waste on the structural qualities of sandcrete blocks [9], and the utilization of discarded plastic wastes for the manufacturing of interlocking paving stones [10] are all revealed in studies. Nadimalla et al. [11] (2019)

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concluded that using PET bottles instead of sand in concrete will increase the physical behavior and performance of recycled concrete compared to normal concrete.

Furthermore, the use of artificial intelligence including Artificial Neural Network (ANN) has been reported to provide a faster, cost effective and more reliable alternative to rigorous laboratory testing when used to model the properties of concrete [12-16]. Artificial Neural Network (ANN) is a soft computing technology that uses densely interconnected processing units (neurons) to solve particular problems [17] by replicating the mental processes of pattern recognition and/or reasoning. Self-organizing Mapping (SOM), Radial Basis Function (RBF), Multilayer Perceptron (MLP), and Neuro-Fuzzy are the most often utilized ANN models. This study investigated the multilayer feedforward neural network (MLFFNN) and radial basis function (RBF) approaches for modeling the tensile strength of concrete built using PET waste as a fine aggregate replacement (up to 50%).

2. EXPERIMENTAL SETUP

2.1. Materials

Dangote brand of Portland limestone cement of grade 32.5 class with specific gravity 3.1 was used. Coarse aggregate of 20 mm size classified as well graded gravel was used while fine aggregate classified as poorly graded sand was used. The PET waste was obtained from domestic PET plastic wastes, the paper around the bottle and the bottle covers were removed before it was then grinded into fine aggregate with the maximum size of 2.36 mm using an industrial grinding machine. As a chemical admixture, MasterRheobuild 858 super-plasticizer was used to increase the workability of the concrete with as little water as feasible. The Superplasticizer was added to the mix at a rate of not more than 1% of the total cement weight. The specifics of the coarse, fine and PET aggregates used were 2.71, 2.65 and 1.34 respectively.

2.2. PET concrete procedure

Concrete mix ratio of 1:1.5:3 (cement: sand: granite respectively) was adopted. The percentage of replacement of fine aggregates by PET waste aggregates were 2%, 4%, 6%, 8%, 10%, 12%, 14%, 16%, 18%, 20%, 22%, 24%, 26%, 28%, 30%, 32%, 34%, 36%, 38%, 40%, 42%, 44%, 46%, 48%, and 50%. Concrete without PET waste serves as the control. All of the concrete samples were made using a 100 x 200 mm cylindrical mold that matched the requirements of BS EN 12390-1:2000 [18]. The moulds were lubricated before being filled with PET waste concrete to make demolding easier. All samples were covered with a plastic sheet after casting and finishing to prevent moisture loss due to evaporation. After 24 hours of casting, the samples were demolded and moved to a curing tank, where they cured for 28 days before being tested for split tensile strength in accordance with British standard.

2.3. ANN modeling procedure

A two-layer neural network (hidden and output) was used to predict compressive strength using an ANN. The numerical data (ANSYS) was fed into the ANN after the input data from the laboratory tests were rectified. Based on the mistake results, the number of neurons in the buried layer was calculated. In order, for the output layer to be one neuron, one output neuron is necessary. The method used historical data in conjunction with current data to forecast compressive strength. MLFFNN and RBF techniques were used to operate the neural network. Following that, the precision of the results from both approaches were compared, and the most precise technique was recommended. The optimum architecture of a back propagation neural network for this study was found by experimenting with different numbers of neurons for different hidden layers.

To minimize overtraining and to measure the confidence in the network's performance, the input data was gathered from the experimental data, with 70% of the data utilized for training, 15% for testing, and 15% for validation. The Sigmoid function was chosen as the activation function in this study. To avoid overtraining, the algorithm learning was supervised (i.e. working toward a specific outcome).

The neural network was trained to match the collection of input data that had been weighted into the networks through repeated weight modifications. Backward propagation of error was used to optimize the weights between the neurons throughout the learning process. Root Mean Square Error was used to calculate the performance of the ANN.

3. RESULTS AND DISCUSSION

3.1. Split tensile strength

The split tensile strength of the created PET concrete is displayed in Table 1. With the exception of PET replacement amounts of 2 percent, 4 percent, 6 percent, 8 percent, 10 percent, 12 percent, 14 percent, and 16 percent, which increased the tensile strength of the concrete in comparison to the control mix, the tensile strength of concrete decreases as the amount of PET replacement increases. The higher ductility and sharp edges of the PET waste particles in contrast to the sand particles in the concrete may be the cause of the increase in tensile strength from 2 to 16 percent PET aggregate replacement [7, 19]. The samples with 18 to 50% replacement of PET show a reduction in split tensile strength. Large quantities of PET particles that gathered in one area, clumped together, and were not distributed evenly are to blame for this behavior. Additionally, the interaction zone between the cement paste and the PET aggregates during bonding is limited by the higher PET replacement [11, 19].

Table 1. Split tensile strength of PET concrete.

S/N	Fine Aggregate Replacement (%)	Tensile Strength (N/mm^2)
1	0	2.77
2	2	2.91
3	4	2.97
4	6	3.02
5	8	3.27
6	10	3.09
7	12	3.13
8	14	2.94
9	15	2.86
10	16	2.79
11	18	2.66
12	20	2.55
13	22	2.48
14	24	2.38
15	26	2.61
16	28	2.31
17	30	2.24
18	32	2.10
19	34	1.96
20	36	1.47
21	38	1.22
22	39	1.38
23	40	1.07
24	42	0.90
25	44	0.74
26	45	0.68
27	46	0.56
28	48	0.47
29	50	0.41
30	55	0.30
31	60	0.22

3.2. Split tensile strength modelling using multilayer feed-forward

3.2.1. ANN architecture

The multilayer feed-forward (MLFF) ANN design for predicting tensile strength is depicted in Figure 1. As indicated in Figure 2, the input variable was one (1), there were eighteen (18) hidden neurons used, one (1) served as the output layer, and the model traversed six (6) epochs. The performance of the neural network depends on the epoch and the quantity of hidden neurons. Up until the best performance was realized and the results were recorded, several settings of these two values were explored. In order, to avoid bias in the modeling of the outcome, these values for were chosen at random throughout the entire procedure.

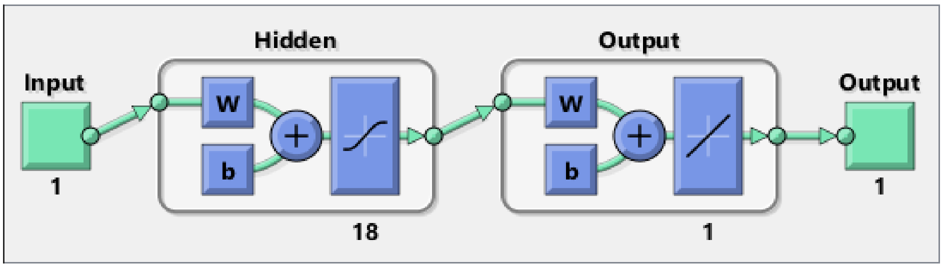

Fig. 1. MLFFNN split tensile test architecture.

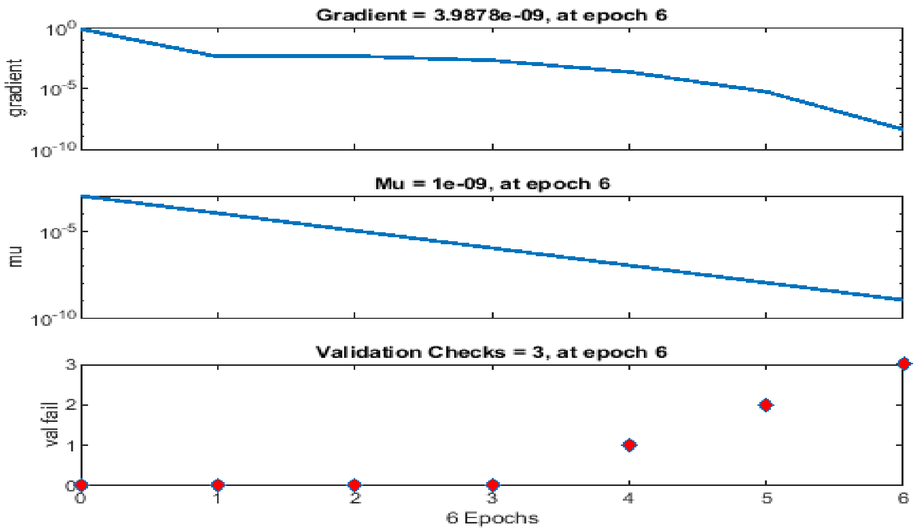

Fig. 2. Epoch for MLFFNN in modelling split tensile strength.

3.2.2. Error histograms

The error histograms for the tensile strength modeling are displayed in Figure 3. The error histogram displayed how close to or far from zero the error was. The discrepancy between the 28-day projections anticipated tensile strength and the actual tensile strength is. The outcome will be more accurate the closer the histograms are to zero. According to the figure, a significant portion of the disparities between the predicted and actual values, particularly for most of the training datasets, lies within the yellow zero line. Little differs between the expected and actual numbers are evident from this.

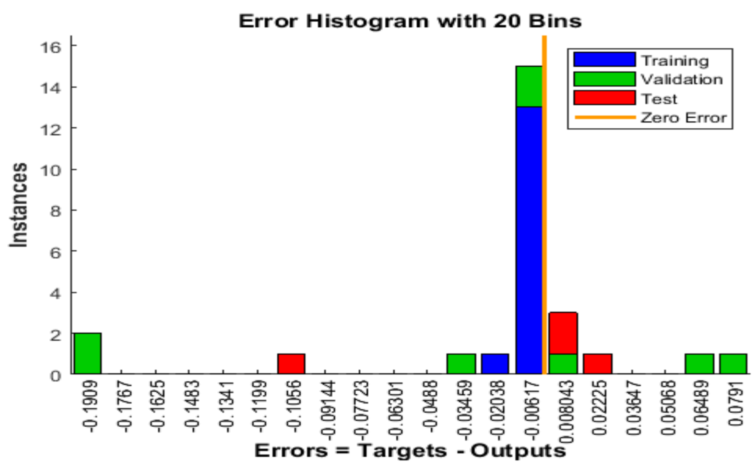

Fig. 3. MLFFNN tensile error histograms for modelling tensile strength.

3.2.3. ANN regression residual plots

Figure 4 displays the residuals for the regression line of fit for the dataset's training, validation, and testing parameters as well as all other parameters. Additionally, it displays the regression's level of accuracy using the provided R score. For all phases (training, testing, validation, etc.), the values above the regression line of fit indicated the values that were properly predicted, whereas the values below the line of fit represented the values that were incorrectly forecasted. Each value's deviation from the line of fit serves as a gauge for its accuracy or imprecision.

In the training phase, the line of fit completely encircled all values, providing a high degree of accuracy of 100 percent. A significant majority of the values for the validation phase fell within the line of fit with a high degree of accuracy of 94.316 percent. The regression model line's accuracy was judged to be 95.364 percent for all values combined, whereas the test has an accuracy level of 87.967 percent. This demonstrated the created ANN model's great capability in estimating the tensile strength of PET concrete given the input variable. The prediction model's RMSE value is displayed in Figure 5. The RMSE score of 4.4409 x 10^{-16} indicated a very low error value that was practically nonexistent. The ability of the MLF ANN model to accurately predict the tensile strength of the PET concrete serves as another example of its capabilities.

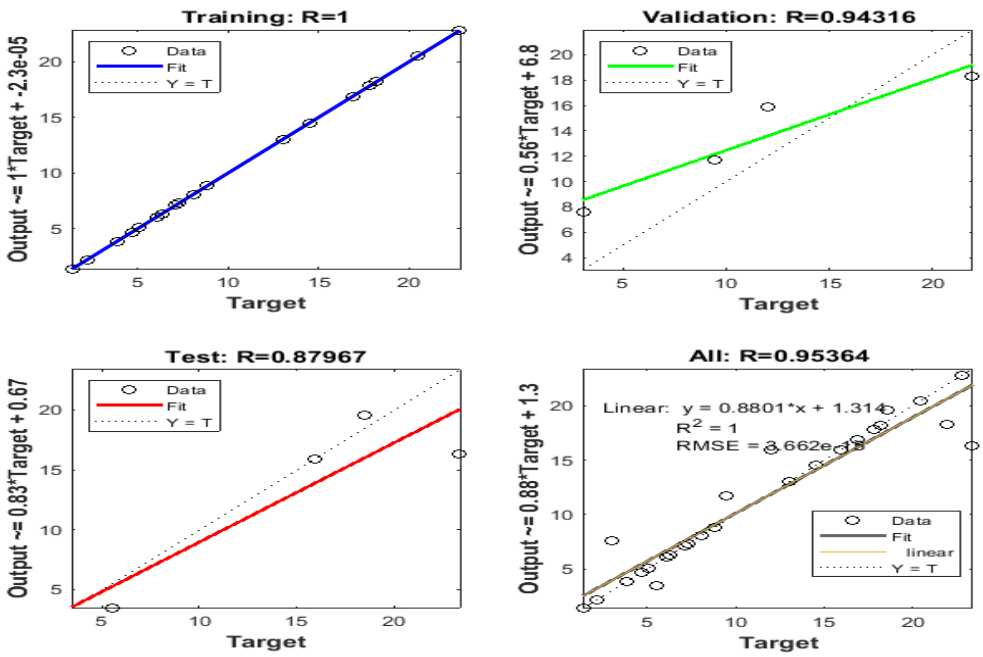

Fig. 4. MLFFNN regression residual plots for modelling tensile strength.

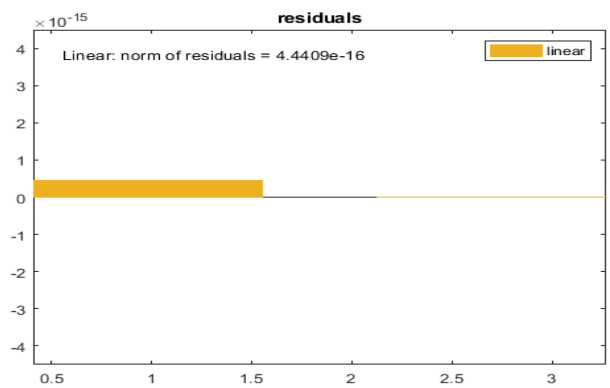

Fig. 5. MLFFNN RMSE for modelling tensile strength.

3.3. Split tensile strength modelling using radial basis function

3.3.1. ANN architecture

Figure 6 shows the radial basis function (RBF) ANN architecture for tensile strength predictions. As indicated in Figure 7, the input variable was one (1), there were twenty hidden neurons employed, one served as the output layer, and the model proceeded through one hundred and sixty one epochs. The performance of the neural network depends on the epoch and the quantity of hidden neurons. Up until the best performance was realized and the results were recorded, several settings of these two values were explored. To avoid bias in the modeling of the outcome, these values were chosen at random throughout the entire procedure.

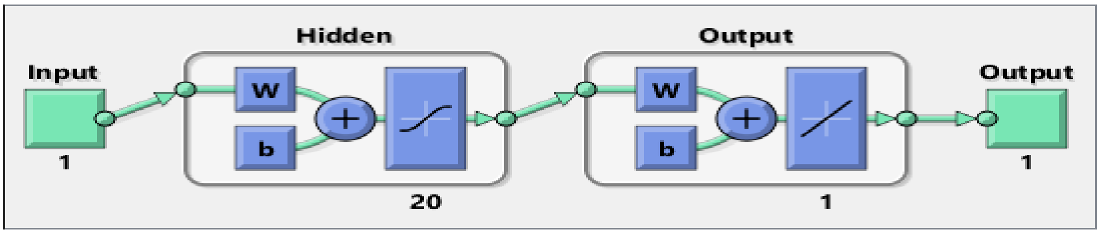

Fig. 6. RBF architecture for modelling split tensile strength.

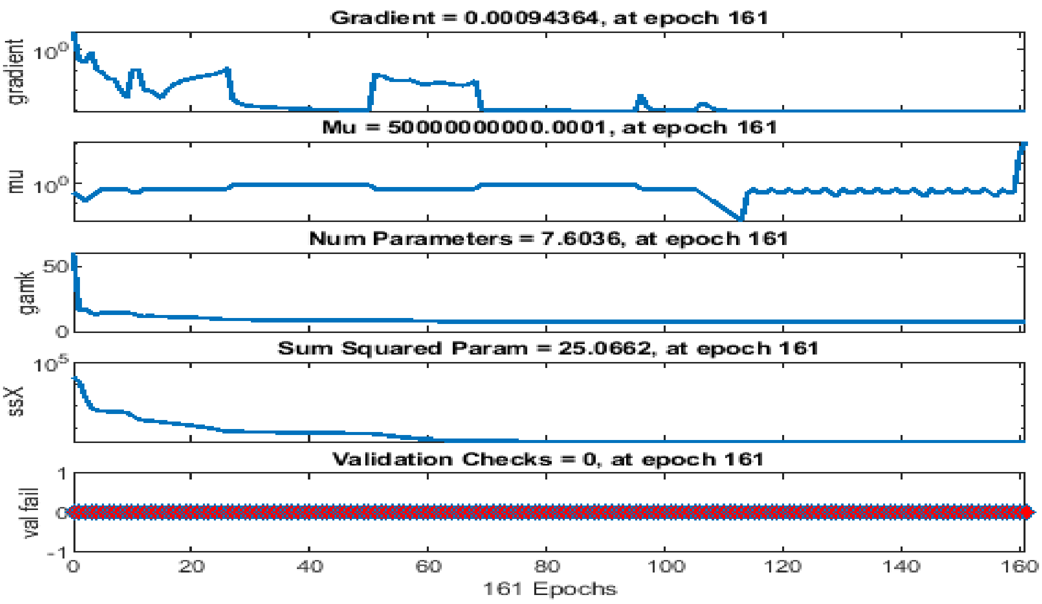

Fig. 7. Epoch for modelling the split tensile strength using RBF.

3.3.2. Error histograms

The error histograms for the tensile strength result are displayed in Figure 8. The error histogram displayed how close to or far from zero the error was. The discrepancy between the 28-day projections' anticipated tensile strength and the actual tensile strength is. The outcome will be more accurate the closer the histograms are to zero. According to the figure, a significant portion of the disparities between the predicted and actual values, particularly for most of the training datasets, lies within the yellow zero line. Little differs between the expected and actual numbers are evident from this.

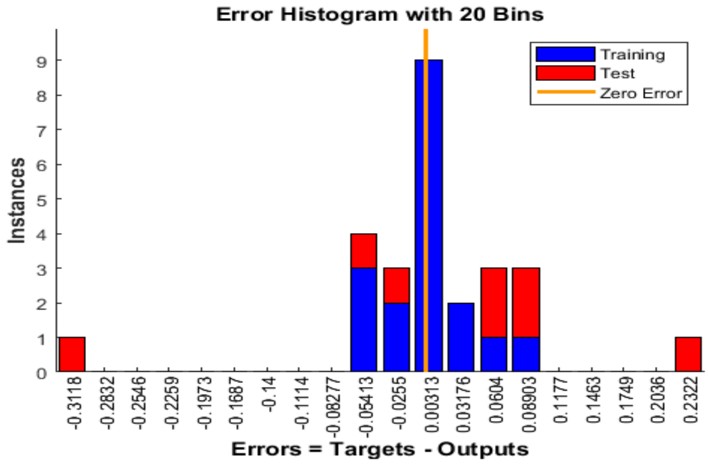

Fig. 8. RBF error histogram with 20 Bins for modelling split tensile strength.

3.3.3. ANN regression residual plots

Figure 9 present the residuals for the regression line of fit for the dataset's training, validation, and testing parameters as well as all other parameters. Additionally, it displays the regression's level of accuracy using the provided R score. For all phases (training, testing, validation, etc.), the values above the regression line of fit indicated the values that were properly predicted, whereas the values below the line of fit represented the values that were incorrectly forecasted. Each value's deviation from the line of fit serves as a gauge for its accuracy or imprecision.

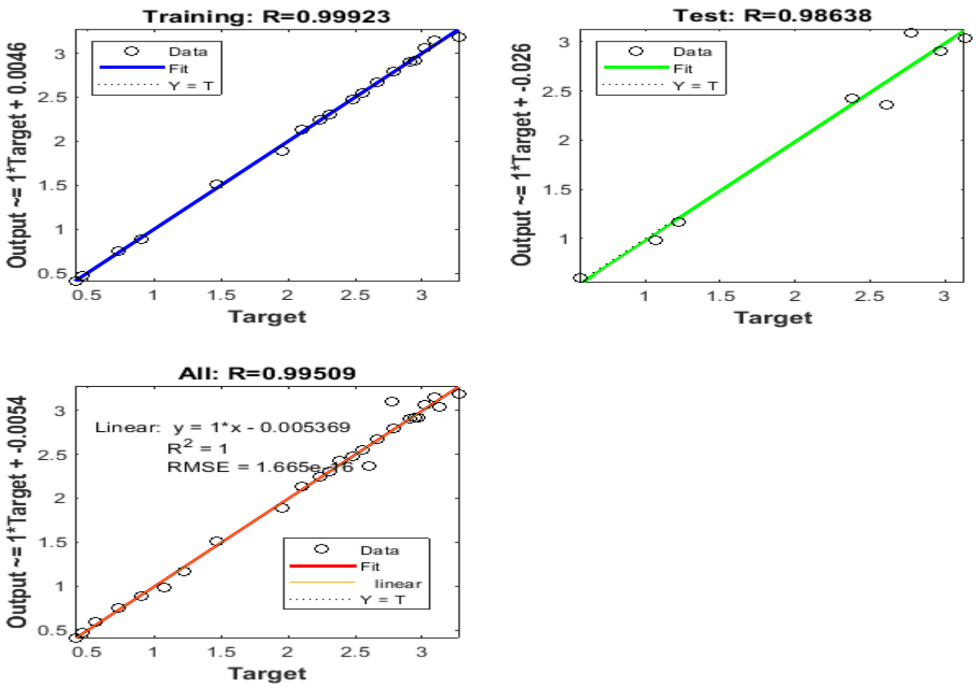

Fig. 9. RBF residual regression plot for modelling split tensile strength.

The line of fit covered all values for the training phase, and accuracy was extremely high at 99.923 percent. The regression model line's correctness was judged to be 99.509 percent for all values combined, whereas the test has a degree of accuracy of 98.638 percent. This demonstrated the constructed ANN model's great capability in estimating the tensile strength values of PET concrete given the input variable. The prediction model's RMSE value is displayed in Figure 10. The RMSE score of 1.6653 x 10^{-16} indicated a very low error value that was practically nonexistent. Additionally, this serves as an illustration of the RBF ANN model's capacity to accurately predict the tensile strength of PET concrete.

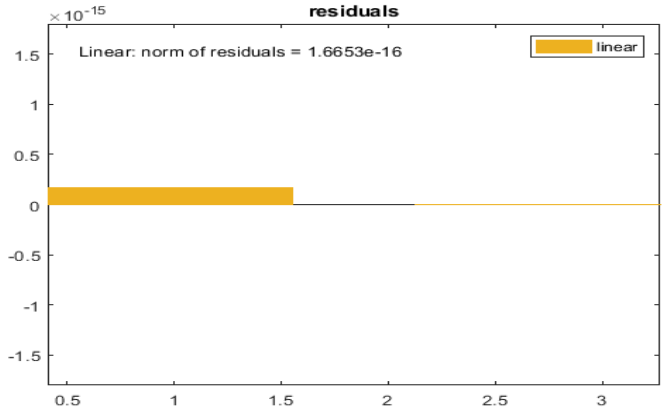

Fig. 10. RBF RMSE for modelling split tensile strength.

3.4. Validation of the model

In comparing the accuracy of the multi-layer feed-forward (MLFFNN) and the radial basis function (RBF) techniques of the ANN in predicting the compressive strength of PET concrete, it was discovered that the RBF was more accurate judging from the values obtained from their error histograms, regression residual plot, and root mean square error values. Hence, in validating the model by predicting for various percentage replacement of fine aggregate with PET, the RBF technique was used. The superior in accuracy of the RBF agrees with past studies from other researchers. RBF analyzes the multiple subspaces of the input set as separate relationships and gives local solution, whereas MLFFNN presents a generic approach to addressing non-linear relationships between the input parameter(s) and output parameter(s).

Tables 2 illustrates the results of the laboratory tests and the predicted results from the ANN for split tensile strength using the more precise radial basis function approach. The projected values from the ANN are without a doubt accurate and dependable for forecasting the compressive strength of PET concrete, since the ANN modeling findings are comparable to laboratory test results. Despite the fact that the RBF approach produced the most desirable results, the MLFFNN's performance was also acceptable.

Table 2. The experimental values and predicted values of split tensile strength for validation.

S/N	**Replacement (%)**	**Lab Result (N/mm^2)**	**ANN Result (N/mm^2)**
1	15	2.86	2.84
2	39	1.38	1.39
3	45	0.68	0.66
4	55	0.30	0.32
5	60	0.22	0.21

4. CONCLUSIONS

This study simulated the split tensile strength of concrete constructed utilizing PET waste as a replacement for fine aggregate using radial basis function (RBF) and ANN with multilayer feedforward neural network (MLFFNN) techniques (up to 50 percent). The design with eighteen (18) hidden neurons and six (6) epochs for 28 days of tensile strength predictions was the best MLP ANN architecture with the highest effective predictive performance. During the training phase, the model's accuracy was 100%. The accuracy of the regression model line was estimated to be 95.364 percent for all the values combined, with the validation phase having a high degree of accuracy of 94.316 percent and the test phase having a degree of accuracy of 87.967 percent. The 28-day tensile strength forecasts' Root Mean Square Error (RMSE) value was 4.4409 x 10^{-16}, which is a very small and nearly negligible error number. This serves as an example of the MLP ANN model's capability to accurately forecast the tensile strength of PET concrete.

The design with twenty (20) hidden neurons and one hundred sixty one (161) epochs for 28 days of tensile strength predictions was the best RBF ANN architecture with the highest effective predictive performance. The model's degree of accuracy during the training phase was 99.923 percent, which during the test phase was 98.638 percent, and that when all the results were combined, the accuracy of the regression model line was estimated to be 99.509 percent. The 28-day tensile strength forecasts' Root Mean Square Error (RMSE) value was 1.6653 x 10^{-16}, which is a very small and nearly negligible error number.

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