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Image Compression Using Different Optimization Algorithms: A Review Artificial Neural Network Modeling of the Compressive Strength of Concrete with Polyethylene Terephthalate (PET) Waste as Fine Aggregate Replacement

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ABSTRACT

This study modelled the compressive strength of concrete with polyethylene terephthalate (PET) waste as fine aggregate replacement. Artificial neural network (ANN) was used to model and predict the compressive strength of PET concrete at various percentage replacements (2 to 50% at a step of 2% by weight), with the multilayer feedforward neural network and the radial basis function methodologies compared to see which is more accurate. The multilayer feedforward neural network modelling results showed a predictive accuracy of 95.364% with root mean square error value of 3.6621×10^{-15} while, the radial basis function neural network modeling results showed a higher predictive accuracy of 99.812% with root mean square error value of 3.7748×10^{-15}. The results of this study demonstrated that computer-generated models such as the radial basis function may accurately predict the compressive strength of PET concrete, as the results of the experimental and predicted tests were similar. Additionally, it was discovered that the radial basis function method takes less time to create the model because there is no repetition required to get at the model's favorable parameters. Furthermore, radial basis function networks train more quickly than multilayer perceptrons, but classification is slower since each hidden layer node must calculate the radial basis function for the input sample vector during classification.

Keywords: Concrete Strength, Computer Model, Neural Network, Plastic waste.

1. INTRODUCTION

The most common building material worldwide is concrete. Cement, water, and aggregates make up its ingredients. About 65 to 80 percent of concrete is made up of aggregate, and it can give concrete great qualities including strength, permeability, volume stability, workability, and durability [1]. A significant number of fine and coarse aggregates are needed to produce enormous amounts of concrete for worldwide consumption [2]. By utilizing recycled resources to create fresh concrete, significant amounts of waste can be saved. This approach can be used to address environmental problems with aggregate mining, waste disposal, and aggregate shortages on construction sites [3, 4]. Numerous different forms of plastic are manufactured each year as a result of the existing demand from human activities. However, the vast majority of plastic varieties are made to be used only once. Because plastic garbage has a very poor biodegradability and cannot be properly recycled, it pollutes the environment. One of the best ways to lessen the impact plastic trash has on the environment in terms of energy and natural resource use, waste disposal, global warming, and environmental contamination is to recycle it. Among the numerous types of recycling management techniques, the reuse of plastic waste in the construction industry is the best choice for disposing of plastic trash [5, 6].

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As was already indicated, recycled plastic aggregates can be utilized successfully to make concrete in order to reduce the consumption of natural aggregates. Several research have been done on the use of waste PET as a complete or partial replacement for different concrete materials. Akinyele et al. [7] investigated how PET waste affected the structural characteristics of burned bricks. Compressive strength decreased as PET waste volume increased. It was found that a good percentage to add to the brick for optimal performance would be less than 5% PET. The effect of partial substitution of fine aggregate with PET in concrete was investigated by Nadimalla et al. [8]. The slump value of the concrete mixtures reduced because of the uneven edges of the PET. Improvement in strength properties of concrete was observed only at less than 10% replacement levels. Akinyele and Toriola [9] investigated the effect of crushed PET in sandcrete bricks as a fine aggregate replacement at 0, 5, 10, 15, and 20%. The compressive and flexural strengths showed that at 5% PET replacement performed better than the control. The effect of waste PET fragments as a partial replacement for fine aggregate was investigated by Azhdarpour et al. [10]. There was an improvement in both the physical and strength properties of concrete when 5 to 10% of waste PET fragments were used. Akinleye et al. [6] evaluated the use of discarded plastic waste for interlocking paving stone production using the proportions of 10%, 20%, 30%, 40% and 50% plastic wastes relative to stone dust. All mixtures of plastic waste relative to stone dust evaluated met the minimum standard of 30 N/mm^2 specified for a single concrete paving stone according to BS code.

Among the several concrete qualities, compressive strength is a crucial quality for building engineering structures. Compressive strength is related to other durability and mechanical factors, and these values can be determined via indirect relationships with it [11]. Since compressive strength is sensitive to mixture proportions and depends on a number of factors, more advanced techniques should be used to minimize the need for laboratory experiments as much as possible and provide engineers with more user-friendly techniques and mathematical formulas for predicting the results of laboratory experiments. Artificial intelligence methods, such as those utilizing Artificial Neural Networks (ANN), may be thought of as a suitable answer in this case. ANN is a potent simulation program created for data analysis and computing to process and analyze information like a human brain. In order to forecast the future behavior of many numerical issues, construction engineering frequently uses this machine learning method [12, 13]. Some researchers have utilized ANN models to predict the compressive strength of various types of concrete, including self-compacting concrete, recycled aggregate concrete, pervious concrete, and fly ash modified concrete [13, 14, 15, 16, 17]. This study modeled the compressive strength of concrete made with PET waste as fine aggregate replacement (up to 50%) using ANN with the multilayer feedforward neural network (MLFFNN) and the radial basis function (RBF) methodologies compared to see which is more accurate. The findings of this study could help prevent the impending destruction of our ecosystem caused by PET waste. The ANN models would offer a quicker and more dependable substitute for the demanding laboratory testing, hence reducing the testing's financial cost.

The work that is being presented is set up as follows: The methodology is provided in Section 2, where the characterization of the materials utilized, the PET concrete experimentation process, and the ANN modeling process were covered. The experimental findings of the compressive strength of PET concrete were discussed in Section 3. Modeling of compressive strength utilizing multilayer feedforward and radial basis function was done after that. For validation, the experimental and predicted compressive strength values were compared. Finally, Section 4 summarizes the main conclusions.

2. MATERIALS AND METHODS

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 specific of the coarse, fine and PET aggregates used were 2.71, 2.65 and 1.34 respectively.

PET Concrete Experimental 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 mm x 100 mm x 100 mm mold that matched the requirements of BS EN 12390-1 [18]. The moulds were lubricated before being filled with PET waste concrete to make demoulding easier. All of the 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 demoulded and moved to a curing tank, where they cured for 28 days before being tested for compressive strength in accordance with British standard.

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. In order 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

Compressive Strength

The compressive strength of the concretes made with PET waste substitution is shown in Table 1. The study discovered that adding PET trash in place of fine aggregate reduces the compressive strength of concrete. A larger interfacial transition zone (i.e., an increase in the surface area of the PET waste particles) in the concrete that allows for the saturation of a greater amount of water in its surface and reduces the bonding ability between the PET waste and the cement paste as compared to the control may be to blame for the steady decline in the compressive strength of the PET concrete as the percentage replacement of the PET aggregate increased. The binding strength between the cement paste and the PET particles is negatively impacted by the smooth surface of the PET particles. The result is consistent with [19, 20, 21, 22, 23, 24, 25].

Table 1: Compressive strength of PET concrete

S/N	Fine Aggregate Replacement (%)	Compressive Strength (N/mm^2)
1	0	23.39
2	2	22.8
3	4	21.96
4	6	20.47
5	8	18.53
6	10	18.22
7	12	17.83
8	14	16.89
9	15	16.45
10	16	15.94
11	18	14.5
12	20	13.03
13	22	12.01
14	24	9.46
15	26	8.87
16	28	8.08
17	30	7.33
18	32	7.11
19	34	6.09
20	36	5.56
21	38	6.33
22	39	5.67
23	40	5.11
24	42	4.68
25	44	3.87
26	45	3.5
27	46	3.04
28	48	2.22
29	50	1.38
30	55	1.21
31	60	1.01

Compressive Strength Modelling Using Multilayer Feedforward

ANN architecture

The multilayer feedforward (MLFF) ANN design for compressive strength predictions is depicted in Figure 1. As indicated in Figure 2, the input variables were one (1), twenty-two (22) hidden neurons were used, and five (5) epochs were traversed by the model. 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 were chosen at random throughout the entire procedure.

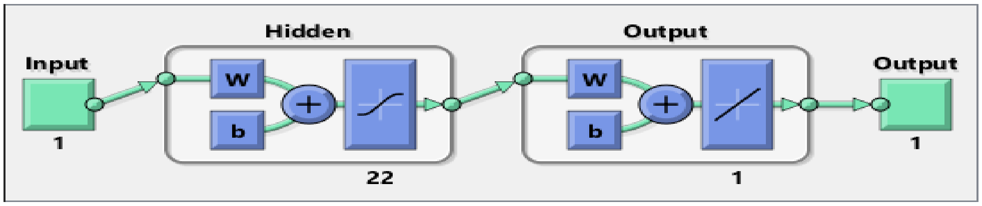


Figure 1: MLFFNN architecture for modelling compressive strength

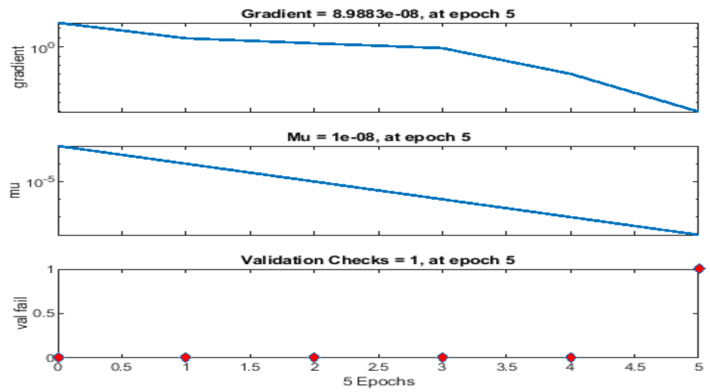


Figure 2: Epoch for modelling compressive strength using MLFFNN

Error histograms

The error histograms for the compressive strength values are displayed in Figure 3. The difference between the anticipated compressive strength and the actual compressive strength for the 28-day forecasts was displayed by the error histogram as a percentage of zero or a distance from zero. The outcome will be more accurate the closer the histograms are to zero. According to the image, notably for the majority of the training datasets, a significant portion of the disparities between the projected and actual values lie under the yellow zero line and zero score. Little differs between the expected and actual numbers are evident from this.

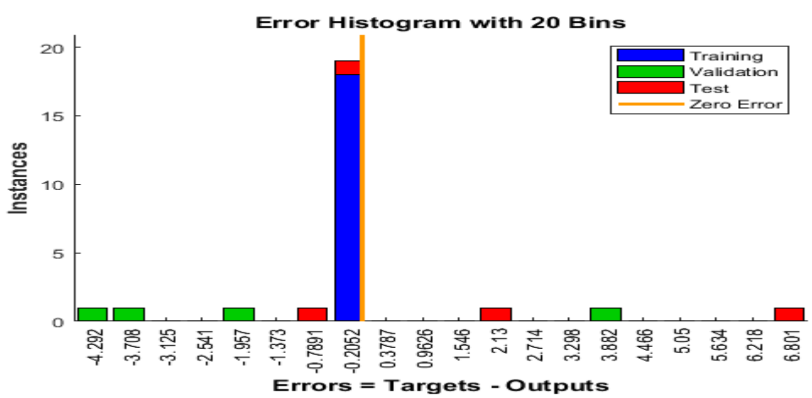


Figure 3: MLFFNN error histograms used for modelling compressive strength

ANN regression residual plots

Figure 4 displays the residual fit for the regression line 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, and validation), the values above the regression line of fit reflected 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.

Nearly all values for the training phase were covered by the line of fit, which was accompanied by a high level of accuracy of 100 percent. With a high degree of accuracy of 94.316 percent during the validation phase, a significant number of the values were inside the line of fit and very few were apart below the line of fit. 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. Given the input variable into the ANN produced model, this demonstrated the great capabilities of the developed ANN model employing the multilayer perceptron technique in estimating the compressive strength of the PET concrete. The predictive model's Root Mean Square Error (RMSE) value is displayed in Figure 5. The RMSE score of 3.6621 10^{-15} indicated a very low error value that was practically nonexistent. This serves as another example of how the MLFFNN ANN model can accurately predict the compressive strength of PET concrete.

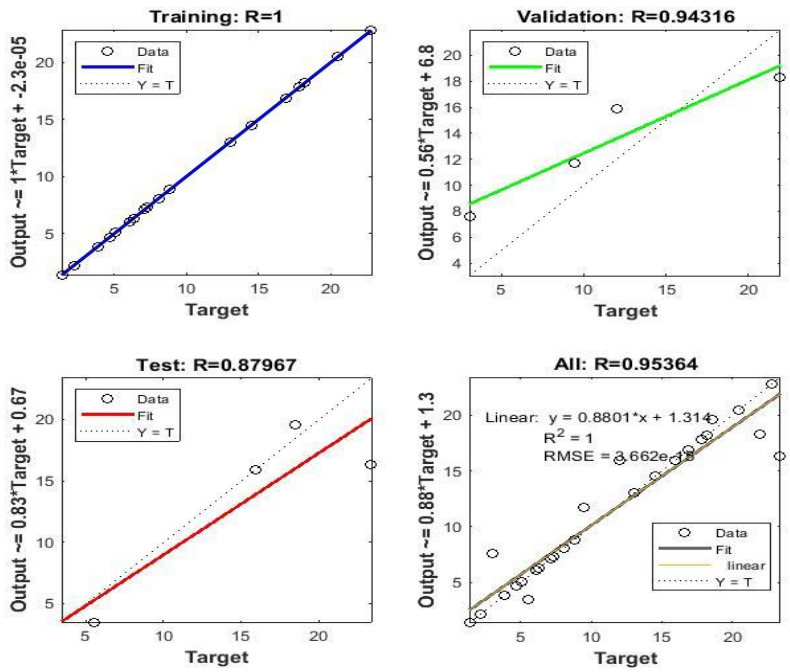


Figure 4: MLFFNN error regression residuals plot for modelling compressive strength

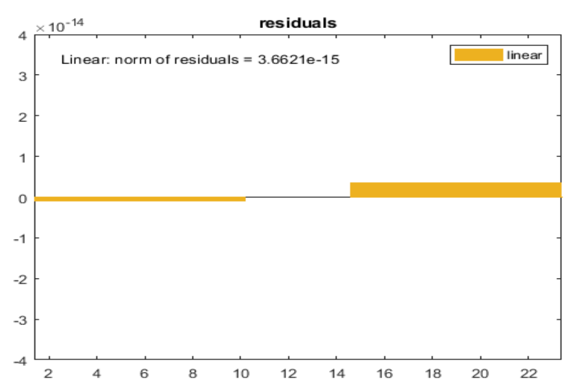


Figure 5: MLFFNN Root Mean Square Error (RMSE) value for modelling compressive strength

Compressive Strength Modelling Using Radial Basis Function

ANN architecture

The Radial Basis Function (RBF) ANN design for the prediction of compressive strength is depicted in Figure 6. As indicated in Figure 7, the input variable was one (1), there were eighteen hidden neurons employed, and the model went through five hundred seventy-two (572) 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 modelling of the outcome, these values were chosen at random throughout the entire procedure.

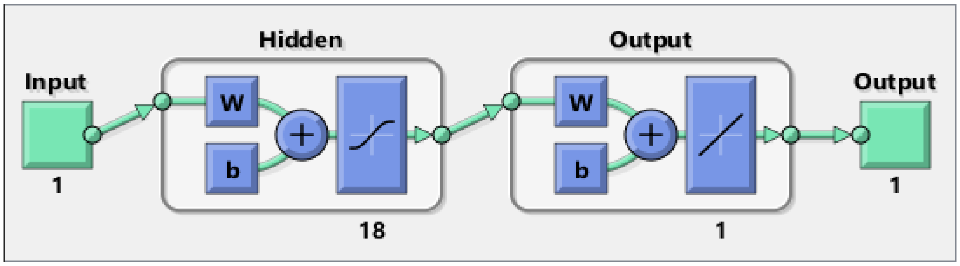


Figure 6: RBF architecture for modelling compressive strength

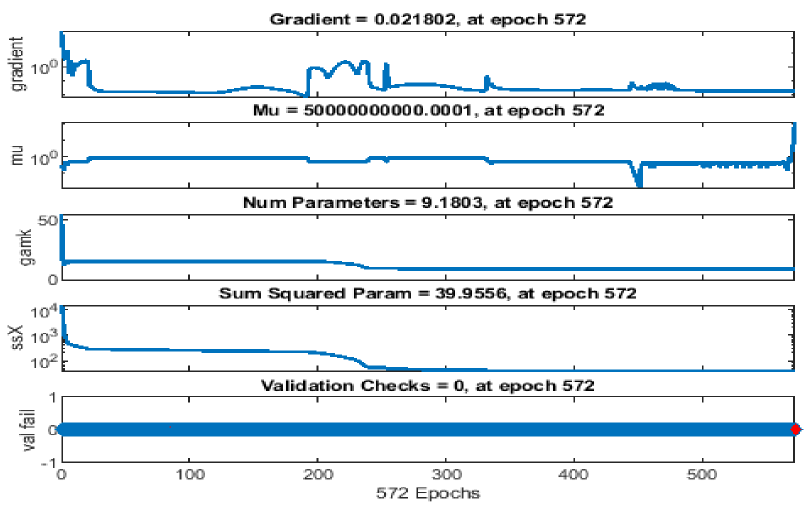
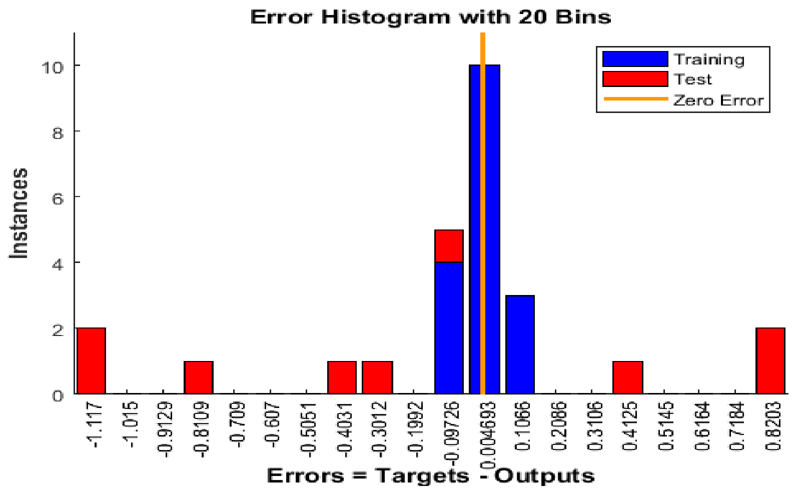


Figure 7: Epoch for modelling compressive strength using RBF

Error histograms

The error histograms for the compressive strength result obtained using the radial basis function technique are shown in Figure 8. The discrepancy between the anticipated compressive strength and the actual compressive strength for the 28-day forecasts is displayed by the error histogram as a percentage of zero or a distance from zero. The outcome will be more accurate the closer the histograms are to zero. The chart shows that a sizeable share of the disparities between the predicted and actual values, particularly for the majority of the training datasets, fall below the yellow zero line. Little differs between the expected and actual numbers are evident from this.



ANN regression residual plots

Figure 9 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.

Nearly all data for the training phase were covered by the line of fit, which was accompanied by a high level of accuracy of 99.998 percent. The regression model line's correctness was evaluated to be 99.812 percent for all values combined, whereas the test has a degree of accuracy of 99.499 percent. This demonstrated that the radial basis function technique outperformed the multilayer perceptron technique at estimating the compressive strength values of PET concrete. The prediction model's RMSE value is displayed in Figure 10. The RMSE score of 3.7748 10^{-15} indicated a very low error value that was practically nonexistent. The ability to accurately estimate the compressive strength of PET concrete serves as another example of the RBF technique of the ANN model in action.

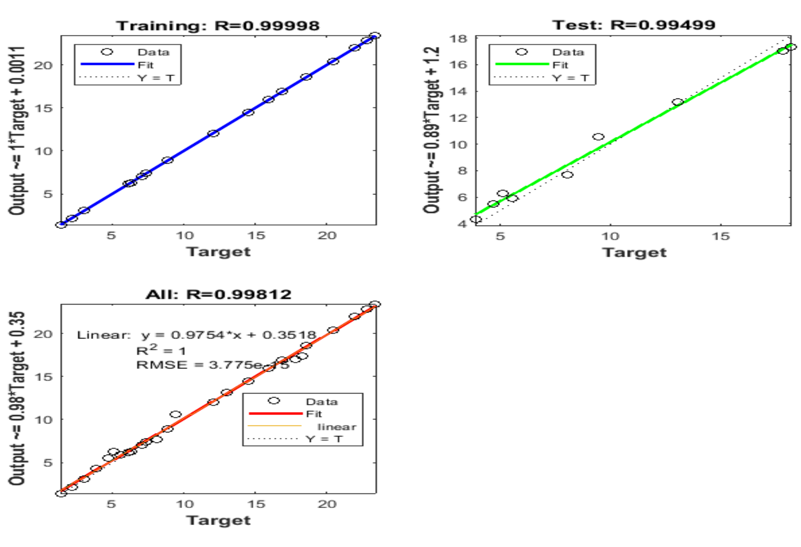


Figure 9: Error regression residuals plot for modelling compressive strength using RBF

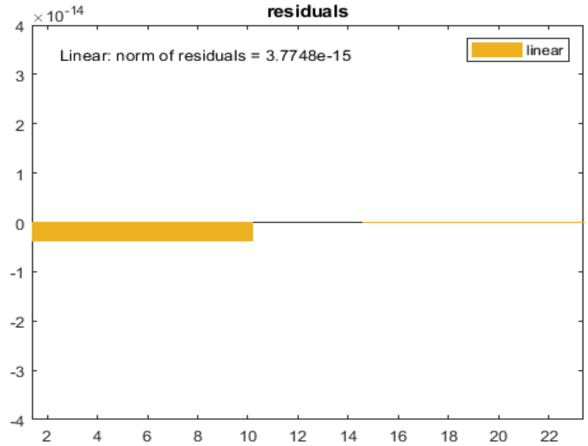


Figure 10: Error RMSE for modelling compressive strength using RBF

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 compressive strength using the more precise radial basis function approach, respectively. 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 compressive strengths for validation

S/NO	Replacement (%)	Lab Result (N/mm^2)	ANN Result (N/mm^2)
1	15	16.45	16.44
2	39	5.67	5.67
3	45	3.5	3.76
4	55	1.21	1.24
5	60	1.01	1.08

4. CONCLUSION

This study used radial basis function (RBF) and ANN with multilayer feedforward neural network (MLFFNN) approaches to simulate the compressive strength of concrete built using PET waste as fine aggregate replacement (up to 50%). The design with twenty-two (22) hidden neurons and five (5) epochs for compressive strength prediction was the best MLP ANN architecture with the highest effective predictive performance. During the training phase, the model's accuracy was 100%. The test phase's accuracy was 87.967 percent, while the validation phase's accuracy was a high 94.316 percent. The regression model line's accuracy was calculated to be 95.364 percent for all values combined. The compressive strength predictions' Root Mean Square Error (RMSE) value was 3.6621 10^{-}

15, which is a very low error value that is practically nonexistent. This serves as an example of the MLP ANN model's capability to accurately predict the compressive strength of PET concrete.

The architecture with 18 hidden neurons and 572 epochs for compressive strength predictions was the ideal RBF ANN architecture with the highest effective predictive performance. The accuracy of the regression model line was estimated to be 99.812 percent for all values combined. The model had a degree of accuracy of 99.998 percent during the training phase and a degree of accuracy of 99.499 percent during the test phase. The compressive strength predictions' Root Mean Square Error (RMSE) value was $3.7748\ 10^{-15}$, which is a very small and nearly undetectable error. RBF technique of ANN fared better than MLFFNN approach.

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