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# Optimization of Tuff Stones Content in Lightweight Concrete Using Artificial Neural Networks

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**Abstract**

Tuff stones are volcanic sedimentary rocks formed by the consolidation of volcanic ash. They possess unique geological properties that make them attractive for a variety of construction and architectural applications. Considerable amounts and various types of Tuff stones exist in the eastern part of Jordan. However, the use of Tuff stones often requires experimental investigations that can significantly impact the accuracy of their physical and mechanical characteristics. To ensure consistent and predictable properties in their mix design, it is essential to minimize the effects of these experimental procedures. Artificial neural networks (ANNs) have emerged as a promising tool to address such challenges, leveraging their ability to analyze complex data and optimize concrete mix design. In this research, ANNs have been used to predict the optimum content of Tuff fine aggregate to produce structural lightweight concrete with a wide range (20 to 50 MPa) of compressive strength. Three different types of Tuff aggregates, namely gray, brown, and yellow Tuff, were experimentally investigated. A set of 68 mixes was produced by varying the fine-tuff aggregate content from 0 to 50%. Concrete cubes were cast and tested for their compressive strength. These samples were then used to form the input dataset and targets for ANN. ANN was created by incorporating the recent advancements in deep learning algorithms, and then it was trained, validated using data collected from the literature, and tested. Both experimental and ANN results showed that the optimum content of the various types of used Tuff fine aggregate ranges between 20 to 25%. The results revealed that there is a clear agreement between the predicted values using ANN and the experimental ones. The use of ANNs may help to cut costs, save time, and expand the applications of Tuff aggregate in lightweight concrete production.

*Keywords:* Volcanic Tuff; Lightweight; Concrete; Artificial Neural Networks; Compressive Strength.

## 1. Introduction

Lightweight concrete is a creative solution to reduce the self-weight of constructions, which can reduce the required size or reinforcement of structural elements, including slabs, beams, columns, and footings. This may lead to considerable savings in terms of cost and environmental impacts, especially for high-rise construction. Other advantages may include enhanced earthquake response, formwork savings, enhanced insulation properties, improved fire resistance, and improved freezing and thawing resistance, to name a few [1, 2]. Considering that aggregate occupies about 70–75% of the concrete's volume [3], lightweight concrete can be produced by using lightweight coarse and/or fine aggregates. Such aggregate can be obtained by naturally occurring porous stones like Tuff and pumice or produced artificially (production of porous aggregate like expanded clay and shale by heat treatment) [4]. Moreover, several agricultural

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wastes, such as palm oil clinker [5], palm oil shells [6], and rice husk ash [7], can be used to produce structurally lightweight concrete.

Tuff stones can be considered one of the naturally occurring lightweight aggregates. Tuff stones are volcanic sedimentary rocks formed from consolidated volcanic ash; they possess unique geological properties that make them characterized by their porous structure [8]. Tuff lightweight aggregate has been successfully used for the production of masonry concrete [9], insulating purposes [2], structural elements [10], and cement replacement material [11]. The production of structural lightweight concrete using Tuff aggregate requires a good mix design that guarantees high-quality paste and good aggregate proportioning. These variables are not only affecting the properties of the produced concrete but also its cost. On the other hand, the brittleness and porous nature of Tuff aggregate require the investigation of how to produce high-performance lightweight concrete using such aggregate [2]. Accordingly, many trial mixes should be investigated to optimize the produced concrete. The number of required trial mixes may quite increase since a standard procedure is not yet available for each type of lightweight aggregate used. This is attributed to the complex nature of lightweight aggregates, especially the naturally occurring types existing in different parts of the globe. Lightweight aggregate properties may change depending on its origin, mineral composition, and formation mechanism [12]. This may limit the use of such aggregate for massive lightweight concrete manufacturing, especially with the absence of accurate models to predict its mechanical properties. The experimental investigations of the mechanical properties of such concrete may require huge amounts of effort, time, and cost, which should be minimized as much as possible. Additionally, the development of prediction models based on laboratory experiments is usually based on regression analysis and does not always provide accurate results [13]. These reasons increase the potential of using machine learning methods to predict the properties of lightweight concrete [12].

Artificial neural networks (ANNs) have emerged as a promising tool to address such challenges, leveraging their ability to analyze complex data. ANNs can provide both linear and nonlinear modeling capabilities, all without necessitating prior knowledge of the connections between input and output variables [13]. ANNs have been used for several applications in civil engineering, including the prediction of mechanical properties [14, 15], carbonation depth estimations [16], crack detection [17], the prediction of stress-strain behavior [18], deterioration prediction [19], and many other applications.

The mix design of lightweight concrete using Tuff has traditionally relied on empirical knowledge and trial-and-error approaches. These methods, while valuable in some cases, often lack precision and reproducibility, resulting in variations in mix-design outcomes. In recent years, researchers have explored the use of ANNs to optimize the mix design of conventional concrete and provide a more systematic and data-driven approach [20, 21]. Recent developments in deep learning algorithms, such as convolutional neural networks (CNNs) and recurrent neural networks (RNNs), present opportunities to enhance the modeling capabilities and prediction accuracy for concrete mix-design outcomes [21, 22].

Few studies can be found in the literature regarding the application of ANNs in the prediction of the mechanical properties of concrete produced using Tuff aggregate. An investigation on the prediction of the compressive strength of concrete using ANN was conducted by Ceylan [23]. In this research, Tuff aggregate was used as a mineral additive in the form of powder as a cement supplementary material. The results of both ANN and experimental work provided that the highest compressive strength could be achieved by adding 20% of the Tuff powder. A similar investigation on the use of volcanic ash was conducted by Amin et al. [12], but on mortar specimens. ANN and adaptive neuro-fuzzy interface systems were used. The results provided that the optimum volcanic ash content was 22%, and it shows the least effect on the compressive strength as compared with other variables including age, curing temperature, and water-to-cement ratio. Many of the other available ANN studies have considered the use of natural pozzolans like natural zeolite [24, 25], fly ash [26], and volcanic Scoria [27], to mention a few. The available existing studies have considered the use of ANN to predict the properties of Tuff ash as a cement replacement material, but none of them considered the use of Tuff as a fine or coarse aggregate replacement. There are still avenues for further research.

The investigations and applications of high-strength lightweight concrete are attracting a lot of interest due to the accelerated demands of urban development. There is an indispensable necessity to create accurate and fast techniques to predict the compressive strength of lightweight concrete. This study aims to minimize the work required to produce lightweight concrete using different types of naturally occurring Tuff stone as fine aggregate. To achieve this goal, an advanced ANN model was created based on experimental data and by incorporating recent advancements in deep learning algorithms to accurately predict the compressive strength, determine the optimum Tuff content, and produce high-strength concrete. A dataset of the measured compressive strength based on the results of 68 concrete mixtures was generated and used for the model creation. These mixtures were produced by varying the content and type of Tuff fine aggregate. The model was further validated using experimental values drawn from the available published research. The findings of this research will contribute to the growing body of knowledge on using the Tuff Stone by means of ANN and initiate a dataset that can be used for future research.

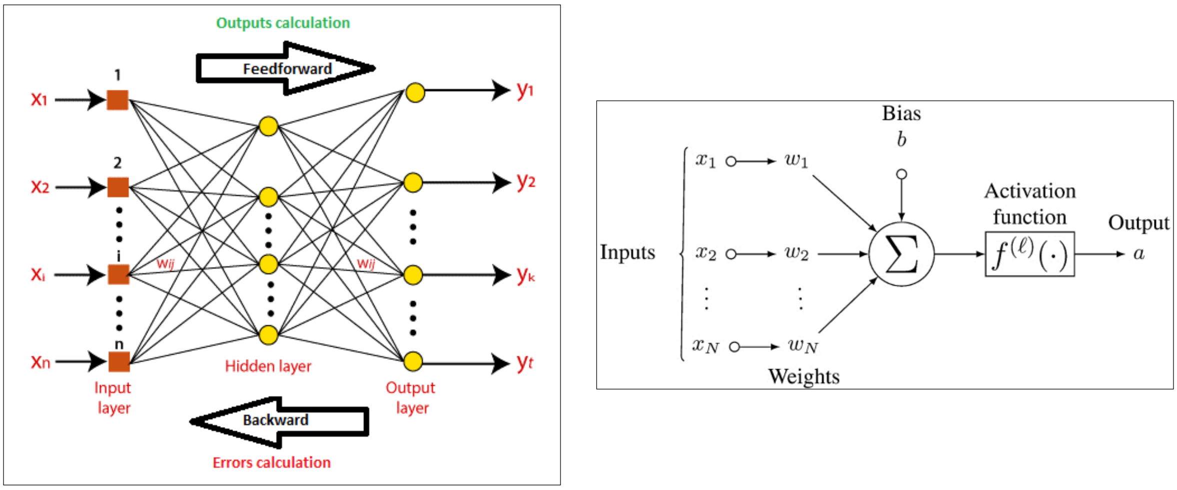
## 2. Materials and Methods

### 2.1. Experimental

The concrete mixtures were manufactured using ordinary Portland cement (Type 1), crushed gray Tuff coarse aggregate, a mix of silica sand and crushed tuff for the fine aggregate, superplasticizer, and water. The maximum aggregate size, bulk specific gravity, and absorption of the coarse aggregate were 16mm, 1.61, and 12.82%, respectively. The fine aggregate comprises a mix of silica sand and crushed Tuff at ratios starting from 0% of Tuff and increasing up to 50% tuff at increments of 10%. Three types of crushed fine Tuff aggregate were investigated in this study. These Tuffs can be classified based on their colors into gray, brown, and yellow. The bulk specific gravity and absorption of the gray, brown, and yellow Tuffs were 2.21 and 11.06%, 2.05 and 25.09%, and 2.16 and 17.65%, respectively. Tuff aggregates were acquired from quarries located in the eastern north of Jordan. Both fine and coarse aggregates satisfy the grading requirements of ASTM C330 standards [28]. The specific gravity and absorption tests were conducted in accordance with ASTM C127 [29]. The superplasticizer was added at a ratio of 1.5% of the cement weight. The cement content was increased from 300 to 450 kg/m$^3$ at increments of 50 kg to produce concrete with a targeted compressive strength of 20, 30, 40, and 50 MPa. A total of 68 concrete mixes were produced, and the cubic compressive strength for each mix was estimated as an average of at least three cubes at 28 days in accordance with ASTM C39 test procedures [30].

### 2.2. Artificial Neural Network (ANN)

ANN is a powerful mathematical model that can be easily used to predict the targets of any experimental set, including volcanic tuff testing [21]. ANN consists of a set of fully connected neurons; each connection has a weight, and the neurons are arranged in a selected number of layers, as shown in Figure 1-a. Each neuron in ANN performs two operations, as shown in Figure 1-b. The first includes the summation of the products of each input with the associated weight. The second is to apply the activation function used for the ANN layer to generate the output. The activation function can be linear, logsig, or tansig. In the case of the linear activation function, the output will equal the summation, while in the case of logsig and tansig activation functions, the output can be calculated by the functions shown in Figure 2 [31, 32].




(a) (b)

**Figure 1. (a) ANN architecture, and (b) ANN neuron operations [32]**

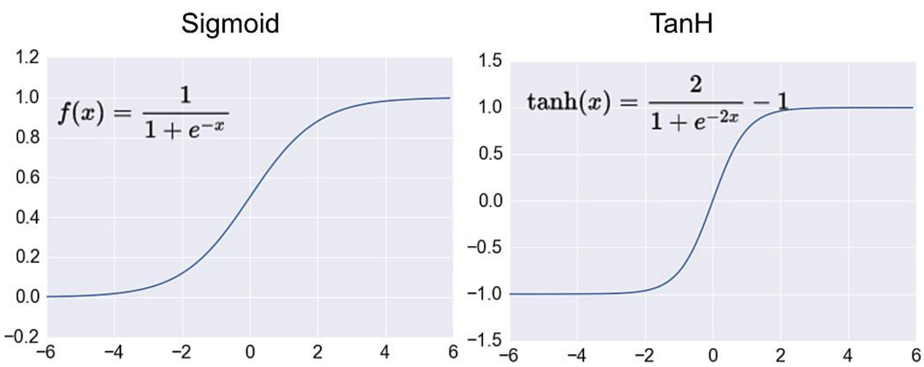
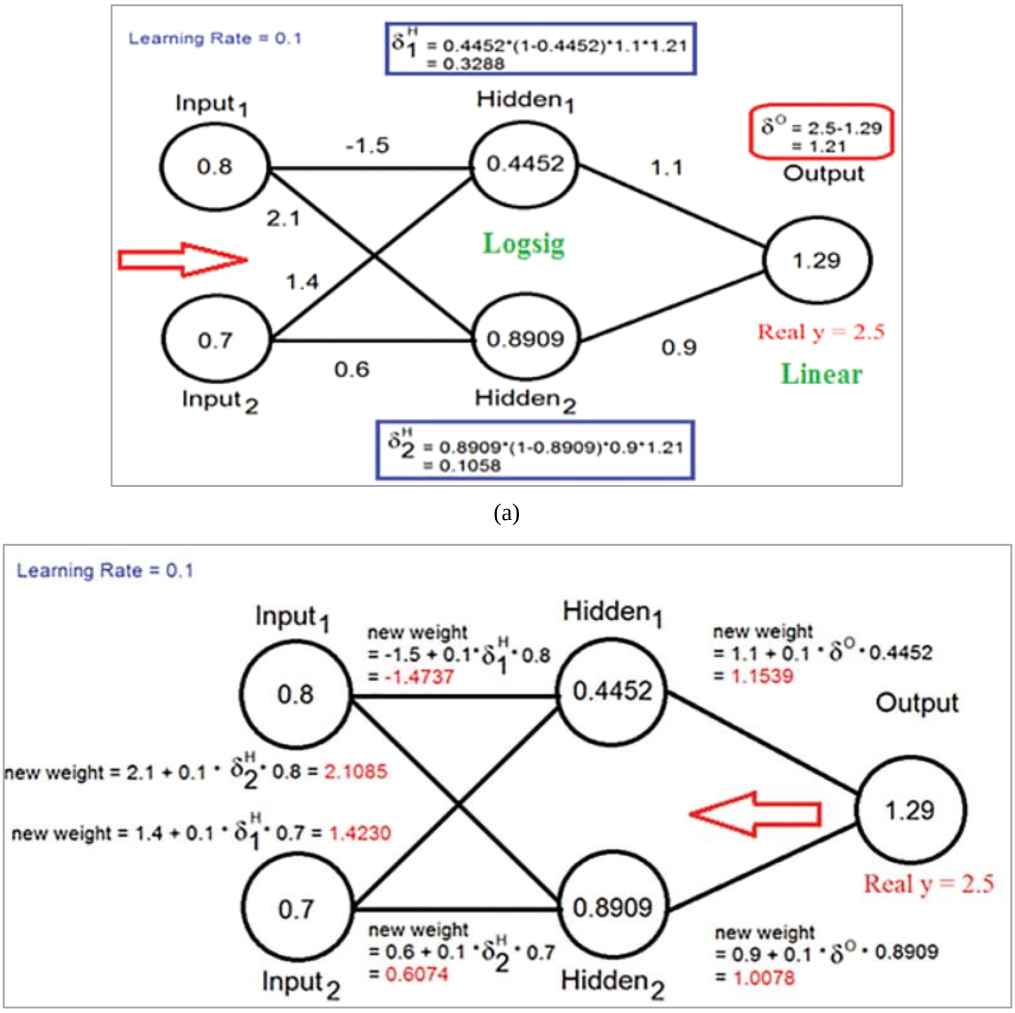



**Figure 2. Activation functions of Logsig (left), and Tansig (right) [32]**

ANNs are used in many applications, including output prediction, which means predicting the required output using a selected experimental input dataset. ANN can be treated as a black box with a set of data inputs and a set of calculated targets (outputs). The outputs of ANN are to be calculated from the input layer toward the output layer (forward calculations). The calculated outputs will be compared with the selected target; if the mean square error between the outputs and the target satisfies the requirements, the training will be stopped. Otherwise, the error will be calculated, and the weights will be updated starting from the output layer and ending with the input layer (backward calculations). Figure 3 shows one ANN training cycle [31, 32]:




(b)

**Figure 3. Calculation of neuron outputs, and (b) calculation of errors and updating of weights [32]**

## 2.3. Building a Prediction Tool

Figure 4 illustrates the required procedures to build an ANN model to be used as a prediction tool. The first step is to collect the required experimental data. These data should be arranged in a 2D matrix; a column should be created for the value of each experimental sample, and the number of rows will point to the number of samples. Another matrix with an m column will be required, in which m represents the number of targets. The second step is to normalize the data to make the values of the input data small within the 0 to 1 range. This will be conducted by dividing the input data by the maximum value. The third step is to create the ANN architecture. This step requires the selection of the number of layers, the number of neurons in each layer, and the suitable activation function for each layer. The fourth step is to determine the required ANN parameters, especially the Mean Squared Error (MSE) and the number of training cycles. The fifth step is to train the ANN model. If the MSE is acceptable, then this ANN will be saved to be used later as a prediction tool; otherwise, it is required for the next step, in which another training cycle will be executed, and the results will be returned as inputs to the previous step (step 5). The last step is to check if the MES requirements are satisfied; if so, then the model is ready. Otherwise, the ANN architecture should be changed by modifying the number of layers, changing the activation functions, or increasing the number of selected training cycles and then repeating the training process.

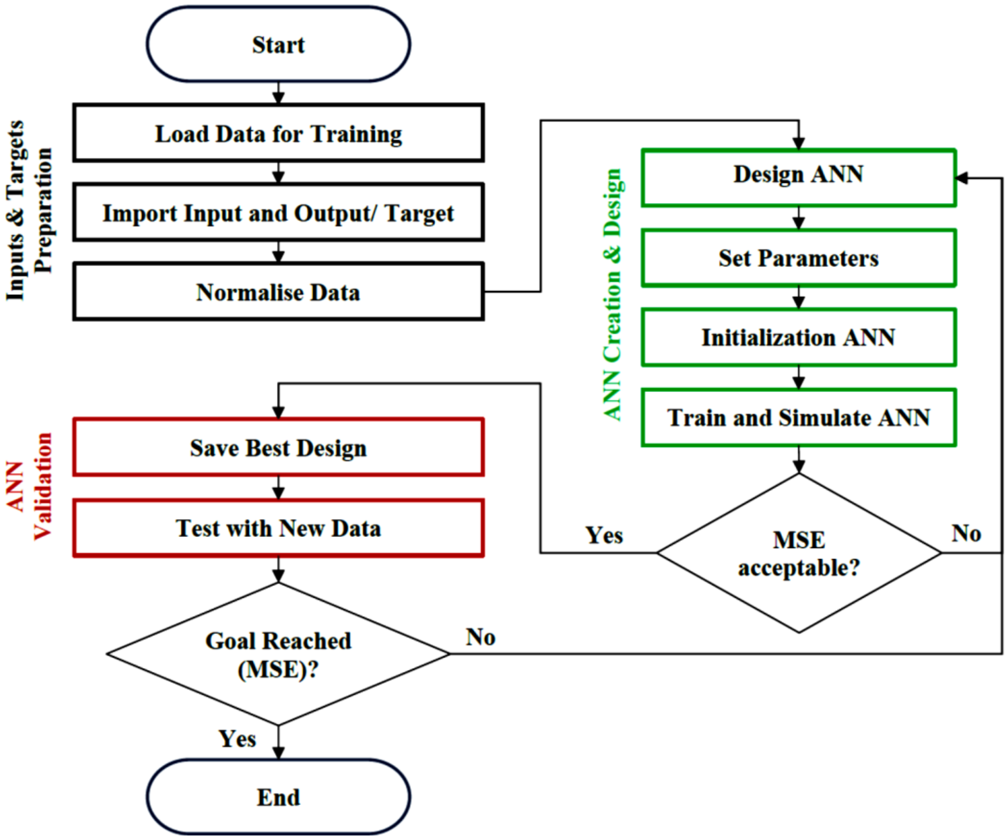



**Figure 4. Flowchart of ANN predictor building and training**

## 2.4. Implementation of the ANN Model Using MATLAB Software

The results of the 68 concrete mixes were obtained. The details of the concrete mixes including the Tuff fine aggregate content were used as input dataset. The measured compressive strength and the estimated percentage change in compressive strength with reference to the control specimen (0% Tuff) were used as the output dataset. These values are given in Tables 1 and 2. These datasets were used to form the inputs and the outputs of ANN using two ANN methods: Feed Forward (FF) and Cascade Forward (CF). ANN was trained, validated, and tested using the experimental dataset and new data obtained from available literature. The following MATLAB code was used to create, train, and test ANN:

```
%load experimental data b
in=b(1:3,:);
tar=b(4:5,:);
net = newff(in,tar,6);
net.trainParam.epochs = 300;
net.trainParam.goal = 0;
net = train(net,in,tar);
r=sim(net,in);
[mm1 mm2]=PSNR_RGB(r,tar)
```

**Table 1. Experimental and Simulated ANN (FF and CF) output of compressive strength results**

| Concrete Grade MPa | Tuff % | Brown Tuff Compressive Strength (MPa) | | Gray Tuff Compressive Strength (MPa) | | Yellow Tuff Compressive Strength (MPa) | |
|---|---|---|---|---|---|---|---|
| | | Experimental | ANN | Experimental | ANN | Experimental | ANN |
| 20 | 0 | 20.6 | 20.6 | 20.6 | 20.6 | 20.6 | 20.6 |
| | 10 | 24.0 | 24.0 | 21.9 | 21.9 | 21.2 | 21.2 |
| | 20 | 24.3 | 24.3 | 24.0 | 24.0 | 24.7 | 24.7 |
| | 30 | 20.1 | 20.1 | 20.1 | 20.1 | 20.7 | 20.7 |
| | 40 | 17.7 | 17.7 | 18.7 | 18.7 | 19.1 | 19.1 |
| | 50 | - | - | 17.8 | 17.8 | 17.1 | 17.1 |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| 30 | 0 | 33.8 | 33.8 | 33.8 | 33.8 | 33.8 | 33.8 |
| | 10 | 36.2 | 36.2 | 32.5 | 32.5 | 33.3 | 33.3 |
| | 20 | 37.9 | 37.9 | 38.1 | 38.1 | 38.7 | 38.7 |
| | 30 | 33.3 | 33.3 | 35.8 | 35.8 | 36.7 | 36.7 |
| | 40 | 27.2 | 27.2 | 34.7 | 34.7 | 33.6 | 33.6 |
| | 50 | - | - | 32.5 | 32.5 | 28.9 | 28.9 |
| 40 | 0 | 43.6 | 43.6 | 43.6 | 43.6 | 43.6 | 43.6 |
| | 10 | 33.8 | 33.8 | 32.8 | 32.8 | 33.2 | 33.2 |
| | 20 | 45.0 | 45.0 | 44.2 | 44.2 | 45.1 | 45.1 |
| | 30 | 42.5 | 42.5 | 42.9 | 42.9 | 42.6 | 42.6 |
| | 40 | 28.6 | 28.6 | 38.9 | 38.9 | 39.8 | 39.8 |
| | 50 | - | - | 37.4 | 37.4 | 34.7 | 34.7 |
| 50 | 0 | 50.1 | 50.1 | 50.1 | 50.1 | 50.1 | 50.1 |
| | 10 | 52.3 | 52.3 | 48.0 | 48.0 | 48.9 | 48.9 |
| | 20 | 56.4 | 56.4 | 54.4 | 54.4 | 55.9 | 55.9 |
| | 30 | 50.7 | 50.7 | 50.7 | 50.7 | 52.8 | 52.8 |
| | 40 | 36.3 | 36.3 | 48.6 | 48.6 | 51.5 | 51.5 |
| | 50 | - | - | 39.8 | 39.8 | 47.2 | 47.2 |

**Table 2. Experimental and Simulated ANN output results of % change in strength**

| Concrete Grade MPa | Tuff % | Brown Tuff % Change in Strength | | Gray Tuff % Change in Strength | | Yellow Tuff % Change in Strength | |
|---|---|---|---|---|---|---|---|
| | | Experimental | ANN | Experimental | ANN | Experimental | ANN |
| 20 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 10 | 14 | 14.0000 | 6.31 | 6.3100 | 2.91 | 2.91 |
| | 20 | 15.2 | 15.2000 | 16.5 | 16.5000 | 19.9 | 19.9 |
| | 30 | -2.4 | -2.4000 | -2.43 | -2.4300 | 0.48 | 0.48 |
| | 40 | -14 | -14.0000 | -9.22 | -9.2200 | -7.28 | -7.28 |
| | 50 | - | - | -13 | -13.0000 | -16.99 | -16.99 |
| 30 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 10 | 6.62 | 6.6200 | -3.84 | -3.8400 | -1.48 | -1.48 |
| | 20 | 10.08 | 10.0800 | 12.72 | 12.7200 | 15 | 15 |
| | 30 | -1.5 | -1.5000 | 5.92 | 5.9200 | 8.58 | 8.58 |
| | 40 | -2.4 | -2.4000 | 2.66 | 2.6600 | -.59 | -.59 |
| | 50 | - | - | -3.84 | -3.8400 | -14.5 | -14.5 |
| 40 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 10 | -14.2 | -14.2000 | -24.77 | -24.7700 | -23.85 | -23.8500 |
| | 20 | 3.21 | 3.2100 | 1.38 | 1.3800 | 3.44 | 3.4400 |
| | 30 | -2.52 | -2.5200 | -1.6 | -1.6000 | -2.29 | -2.2900 |
| | 40 | -52.4 | -52.4000 | -10.78 | -10.7800 | -8.72 | -8.7200 |
| | 50 | - | - | -14.22 | -14.2200 | -20.41 | -20.4100 |
| 50 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| | 10 | 4.2 | 4.2000 | -4.19 | -4.19000 | -2.39 | -2.3900 |
| | 20 | 11.1 | 11.1000 | 8.58 | 8.5000 | 11.58 | 11.5800 |
| | 30 | 1.18 | 1.1800 | 1.2 | 1.2000 | 5.39 | 5.3900 |
| | 40 | -38 | -38.0000 | -2.99 | -2.9900 | 2.79 | 2.7900 |
| | 50 | - | - | -20.56 | -20.5600 | -5.79 | -5.7900 |

The used ANN comprises two layers as shown in Figure 5; the hidden layer with 6 neurons, and the output layer with two neurons, Logsig was used as an activation function for the hidden layer, and the linear activation function was used for the output layer.

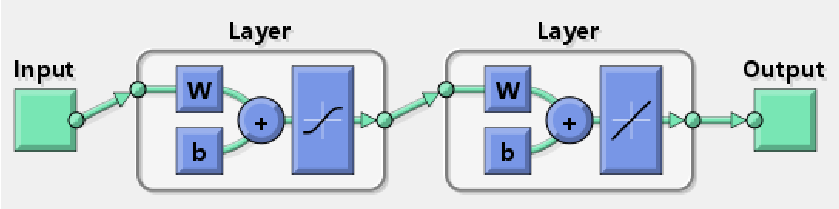



**Figure 5. Used ANN**

## 3. Results and Discussion

The ANN was trained using the selected data sets as given in Tables 1 and 2. The ANN model provided an acceptable result by minimizing the MSE between the calculated (predicted) and the target values, the error as shown in Figure 6 was equal to 0.000093562, which means that the predicted outputs were always close to the target. The ANN simulation provided acceptable results as both training and validation MSE curves have decreased to a stability point as can be seen from Figure 6 and the gap between the curves is small. The curves show no signs of overfitting and the number of training and validation specimens were appropriate to predict the response. The gap between the training and validation curves can be reduced by increasing the number of validation specimens. However, few specimens were found in the literature using the fine Tuff aggregate. Tables 1 and 2 show that the predicted output is very close to the target output and the MSE between them is always close to zero.

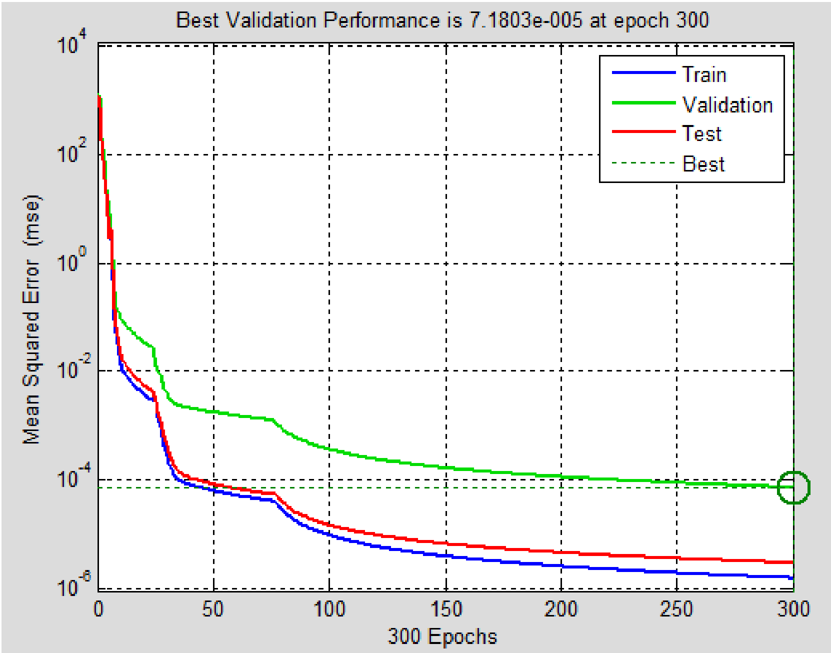



**Figure 6. ANN performance indicator**

## 4. Verification of the Developed ANN Model

To verify the developed ANN model, it was used to predict a new dataset that was collected from available published literature. The collected data included three sets: two for tuff fine aggregate used in all lightweight concrete (LWC) [33, 34], and the third one was for fine tuff aggregate used to replace fine aggregate in normal wight concrete (NWC) [34]. The results of the validation data are given in Table 3. The results provided acceptable predictions of the compressive strength. The use of the ANN-CF method provided lower accuracy than the ANN-FF method, where the error percentage was 0 for all the predicted values using the ANN-FF method, while it ranged from 0.34% to 22.8% when the ANN-CF method was used. These high error values were obtained for the specimen having a Tuff percentage of more than 50%. This was expected since the model was trained on values up to 50% Tuff. Additionally, the number of data points used for the validation processes is low due to the scarcity of available literature. Nevertheless, the ANN-FF method provided high-accuracy predictions, which indicates that the developed model could be used even to predict new data ranges. Figure 7 shows the experimental results, the ANN-predicted results using the ANN-CF method, and the absolute error value.

**Table 3. Validation results of the developed ANN model using FF and CF methods**

| Reference | Tuff % | Compressive Strength (MPa) | | |
|---|---|---|---|---|
| | | Experimental | ANN-CF | ANN-FF |
| Al-Zboon & Zou'by (2017) [33] | 0 | 34 | 33.8829 | 34.0000 |
| | 25 | 38 | 36.4925 | 38.0000 |
| | 50 | 25 | 22.6242 | 25.0000 |
| | 75 | 18 | 16.0482 | 18.0000 |
| | 100 | 13 | 10.9840 | 13.0000 |
| Tuff used in NWC [34] | 0 | 40.33 | 40.1307 | 40.3300 |
| | 25 | 37 | 36.1015 | 37.0000 |
| | 50 | 36.22 | 32.7484 | 36.2200 |
| | 75 | 32.66 | 25.1959 | 32.6600 |
| Tuff used in LWC [34] | 0 | 27 | 26.8659 | 27.0000 |
| | 25 | 41.88 | 40.9223 | 41.8800 |
| | 50 | 39.7 | 36.5418 | 39.7000 |
| | 75 | 34 | 27.6386 | 34.0000 |

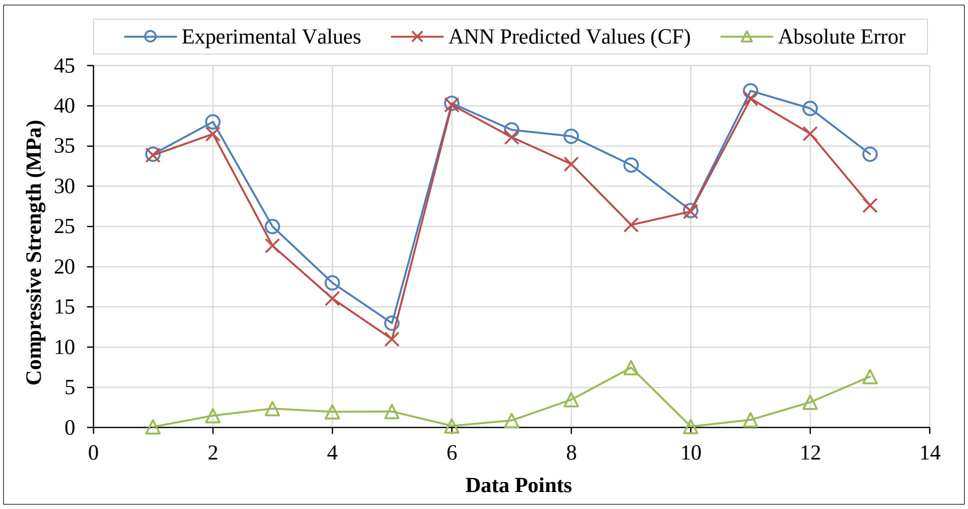



**Figure 7. Validation results using ANN-CF method**

ANN was trained using the selected verification data sets, and it gave an acceptable result by minimizing the MSE between the calculated (predicted) and the target values, as illustrated in Figure 8. The obtained ANN can be used easily as a prediction tool to predict the compressive strength with a significant small error. This tool can be used to minimize the number of required experimental samples and minimize the effort and time of sample collecting. A small number of samples will be sufficient to build and train ANN which will give excellent predicted outputs.

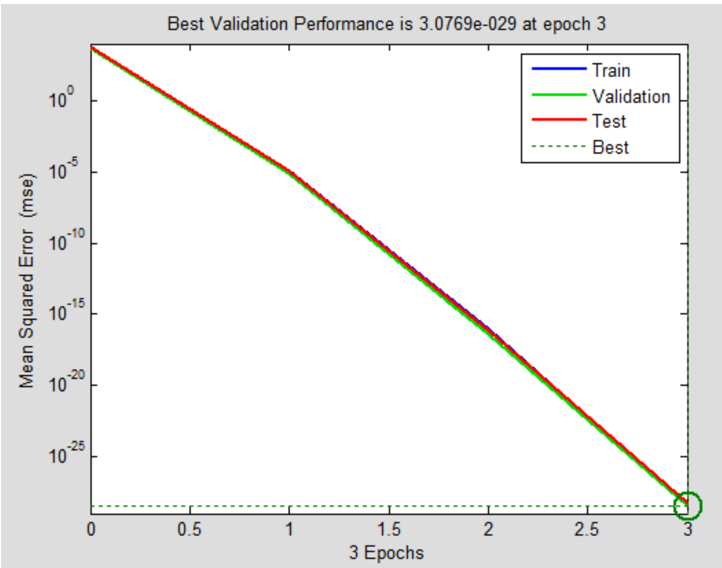



**Figure 8. ANN Performance for the Verification Data Sets**

## 5. Conclusion

In this study, the use of ANNs was evaluated to predict the compressive strength of structural lightweight concrete produced using Tuff fine aggregate at various percentages. The experimental dataset was used to train and test the ANN model, and an additional three sets extracted from the literature were used for the validation model. The results revealed that by using the developed ANN model, the optimum Tuff fine aggregate content can be found when the replacement percentages are in the range of 20 to 25% of the fine aggregate, and this applies for all the used three types of Tuff aggregate. The results show that high-strength lightweight concrete can also be produced based on Tuff aggregate.

The developed ANN model can also be used effectively to predict the compressive strength of structural lightweight concrete based on Tuff aggregate. Based on this model, the predicted outputs are very close to the experimentally measured ones. A zero-error prediction is obtained using the ANN-FF method, while the percentage error does exceed 22% using the ANN-CF method. Based on the validation results, the developed model can be generalized to predict new data with good accuracy.

Human efforts and time are required to get experimental values of the compressive strength of concrete based on Tuff aggregate. The required effort and time will increase, especially when high-strength lightweight concrete is required. The developed ANN prediction model can minimize these efforts and save time by providing accurate predictions. The findings of this research will contribute to expanding the use of natural Tuff aggregate in construction projects; they will also contribute to the growing body of knowledge on using the Tuff stone utilizing ANN and initiate a dataset that can be used for future research.

## 6. Declarations

### 6.1. Author Contributions

A.A.Y., M.T.A., A.B.M., F.R.M., and J.A.A. contributed to the design and implementation of the research, to the analysis of the results and to the writing of the manuscript. All authors have read and agreed to the published version of the manuscript.

### 6.2. Data Availability Statement

The data presented in this study are contained within the article.

### 6.3. Funding

The authors received no financial support for the research, authorship, and/or publication of this article.

### 6.4. Acknowledgements

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### 6.5. Conflicts of Interest

The authors declare no conflict of interest.

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