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ARTIFICIAL INTELLIGENCE-BASED UNCERTAINTY QUALIFICATION OF THE MECHANICAL PROPERTIES OF SUSTAINABLE CONCRETE SPECIMENS

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Abstract

Concrete, as a regular constructional material, can be considered harmful to the environment as it contains cement as the binder ingredient. Utilizing waste materials as a cement alternative in concrete is an environmentally friendly approach to reduce their harmful effects for as long as the lifetime of the concrete structures. Adding waste materials to such sustainable concrete (SC) would change its mechanical properties, which should be estimated. To achieve this goal, in this paper, an extensive database of self-compacting concrete (SCC) specimens containing various dosages of marble stone powder as waste materials and substitution of cement were prepared, and the mechanical properties, including compressive strength, were estimated by artificial neural networks (ANNs). The outcomes showed that the proposed artificial neural network (ANN) model had high performance and low error values and can be utilized as a robust and accurate method.

Keywords: Self-Compacting Concrete (SCC); Artificial Neural Networks (ANNs); Marble Stone Powder; Waste Materials.

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1 INTRODUCTION

Ordinary Portland cement (OPC), aggregate, water, additional ingredients, and chemical additives like superplasticizers make concrete [1–3]. The use of a substantial amount of natural materials and cement in the manufacturing of ordinary concrete (OC) raises issues about pollution problems and sustainability. Carbon dioxide (CO_2) emissions from cement plants are one of the most significant sources of greenhouse gas (GHG) emissions [4,5]. On the other hand, the constant use and extraction of resources substantially impact creatures' natural environments. The building sector is estimated to utilize 60% of the mined resources from the lithosphere [6]. Furthermore, there is a need for concrete that will reduce or eliminate the usage of cement and natural aggregates, transforming the construction sector toward sustainability while simultaneously addressing the challenges mentioned earlier.

Also, as the world's population grows at an exponential rate, governments across the globe are confronted with an ever-increasing amount of waste. Given the massive volume of waste created, using these by-products in manufacturing concrete has a lot of potential in terms of environmental conservation. Waste from the house, business, industry, and construction and demolition waste are the primary sources of these waste products. Given the potential for reuse, most of these waste products are dumped into landfills, which has significant environmental, social, and economic consequences. Inadequate waste handling and mismanagement negatively affect humans, wildlife, and the ecosystem, including health concerns, soil degradation, and water and air contamination [5]. In the concrete industry, various wastes and by-product substances have been widely used to make more ecologically SC as partial or complete replacements for the primary ingredients of the concrete. Using by-products in the building industry will lower total construction costs and mitigate the negative environmental consequences of cement manufacturing, resulting in a more sustainable construction industry.

As previously stated, explosive growth in recent decades has made sustainability a serious challenge. In any community, the building sector substantially affects the development of infrastructure. Concrete has continuously been used as a foundational material in construction [7,8]. Concrete manufacturing produces significant pollution and a large quantity of CO_2, resulting in the depletion of natural resources and the most visible effects on greenhouse emissions. As a result, using industrial waste materials to make SC makes sense [9]. SC is a composite content consisting of cement and other types of binding agents, as well as fine and coarse aggregates, and also certain sustainable admixtures, that is used to improve mechanical properties. Supplementary cementitious materials containing silica-rich components, for example, silica fume (SF) [10,11], fly ash (FA) [12,13], rice husk ash (RHA) [14] and blast furnace slag (BFS) [13,15,16], are by-product pozzolans. Other forms of SCs include recycled aggregate [17–21], waste foundry sand [22], tire rubber [23,24], ceramic [25], granite powder (GP) [26–29], glass sands [21], limestone powder (LP) [30–32], and red mud (RM) [33–35]. Furthermore, waste steel (WS) [36], plastic [37], cotton [38], and carpet fibers [39] have been added to concrete mixes to increase the resistance of concrete under tensile cracking.

The quantitative fluctuation of marble powder and GP with sand and cement was used to evaluate concrete's performance in Singh and Aggarwal's study [29]. Cubes and beams were subjected to flexural and compressive strength (CS) testing. Following 7-days and 28-days of monitoring, the findings revealed that the CS of concrete rose by 17.6 and 14.88 %, respectively, and the flexural strength enhanced by 41.1 and 32.2 %, respectively, in comparison to the control sample. The strength gradually reduced when the percentage of marble and GP was raised. In the Saxena research study [27], mechanical performance assessment experiments like static modulus of elasticity, flexural strength and CS were conducted to examine the impact of the fractional substitution of fine natural sand by industrial fine granite waste powder (FGWP).

Ecological analysis was utilized to calculate the embodied energy (EB-E) and embodied carbon dioxide for the environmental effect evaluation (EB-CO_2). The tests showed that including up to 15% FGWP into geopolymer concrete (GPC) improved mechanical strength and durability. Ferrotto et al. [31] looked into ways to utilize concrete as a waste container, concentrating on waste from limestone quarries and taking on the difficulty of incorporating plastic waste into typical concrete mixtures. The mechanical properties of concrete combined using extra alternative aggregates categorized as waste were researched and addressed in this study to demonstrate the potential of achieving this goal with satisfactory performance loss. The testing findings showed that using plastic waste and limestone quarry waste within large percentage ranges was conceivable, with only a minor drop in strength of concrete, making concrete suitable for various practical uses. Kumar et al. [35] studied the appropriateness of RM to be used in concrete strength augmentation in the existence of FA. Concrete samples were tested for mechanical strength and compared to a control sample. The findings revealed that optimal FA usage leads to increased strength, with the impact being more noticeable in the context of optimal RM dose. As a result, RM in the existence of FA may be employed as a strength booster, lowering cement consumption and resulting in more sustainable construction methods.

ANN has been developed to simulate the human brain. Because of its likeness to the human brain, an ANN that is basic has some robust features in transferring education and understanding. As a result, ANN might be a helpful tool for engineering applications. The earliest development of ANN is thought to have begun around 1943. Later, in 1958, the computer called the perceptron computer was invented, and it operated similarly to the human brain. Inputs, weights, sums, activation functions, and outputs are the five fundamental constituents of an artificial neuron. The organic nervous system inspires these elements. The relation of parts essentially defines the network structure. Neural networks may be given the training to perform a specific job by adjusting the correlations (weights) among components [40]. In applying SC strength forecasting, specific machine learning methods have garnered a lot of attention. They revealed that the MAE percentage of the suggested ANN model for unknown data was below 6%. Golafshani et al. [41] used ANN in conjunction with the multi-objective multi-verse optimizer algorithm to anticipate the compressive strength of SC utilizing waste foundry sand. To estimate the CS, splitting tensile strength and flexural strength of SC, Muhammad et al. [42] suggested multi-expression programming (MEP) optimized employing the particle swarm optimization (PSO) technique. Compared to the original MEP model, the predicted performance was significantly enhanced. Song et al. [43] used four machine learning models to estimate the compressive strength of SC containing FA to evaluate the prediction performance of various algorithms. The bagging regressor model had the best estimate, with $R^2 = 0.95$, compared to the GEP, ANN, and DT models, with R^2 of 0.86, 0.81, and 0.75, respectively. Sarmad [34,35] used three intelligence algorithms to forecast the compressive strength of SC: SVM, long short-term memory (LSTM), and boosted decision tree regression (BDTR). The findings showed that BDTR and LSTM beat the standard SVM model in predicting accuracy, with the CNN LSTM demonstrating the most accurate predicting with the best R^2 and lowest error indices. The work by Singh et al. [40] was conducted to gain better mechanical long-term and desired durability by substituting cement with waste materials (FA and slag). Using 103 datasets gathered from existing technical literature, the ANN was utilized to perform and deliver output for workability and CS of concrete in their study. With the aid of ANN, the goal was to establish the best formula for concrete workability and CS. The importance of RM and glass powder in combination with FA as an aluminosilicate source ingredient for producing GPC was also underlined in Ghosh and Ransinchung's work [34]. Applying machine learning techniques to analyze the 28-day CS data, it was shown that a non-linear model could best anticipate the link between the dependent and the group of independent variables, as evidenced by the highest degree of accuracy (98.79 percent).

In this investigation, the CS of concrete specimens, including various dosages of waste materials such as limestone powder, granite powder, marble powder and red mud, is estimated by the ANN method. In the proposed model, the influence of cement and water contents, fine and coarse aggregates and the curing time are also considered as the input parameters. The performance and the error values of the proposed ANN model will be discussed.

2 EXPERIMENTAL DATASET

In this paper, a dataset including 99 compressive tests done on concrete samples with various dosages of waste materials was compiled from four previous research works of Liu and Poon [44], Sadek et al. [45], Jain et al. [46], and Ghalehnovi et al. [47]. As reported in Table 1, in the compiled dataset, the CS of the concrete specimens is considered as the output, which is affected by various input variables such as cement content (C), water (W), fine and coarse aggregates (FA and CA, respectively), superplasticizers (SP), limestone powder (SL), granite powder (GP), marble powder (MP), red mud (RM) and the curing time (CT). Figure 1 shows the distribution of CS relating to each input parameter. As shown in Figure 1, the selected database covered a wide scattered range of each input which is essential for conducting the ANN model.

Ref.	Number of Speci-mens	C (kg/m^3)	W (kg/m^3)	FA (kg/m^3)	CA (kg/m^3)	SP (kg/m^3)	LS (kg/m^3)	GP (kg/m^3)	MP (kg/m^3)	RM (kg/m^3)	CT (Day)	CS (MPa)
Liu and Poon [44]	20	359	178	635	872	5.6 6.2 6.6 7.2 8.2	0	0	0	0 31.1 62.2 93.4 124.6	7 28 56 90	57.0 to 97.5
Sadek et al. [45]	25	400	180	797 to 900	797 to 900	7.95 to 10.3	0	0 80 120 160 200	0 80 120 160 200	0	7 & 28	28.0 to 63.3
Jain et al. [46]	15	546.79	202.31	169.05 338.10 507.16 676.21 845.26	796.54	6.29 7.38 9.84 12.03	0	0 169.05 338.10 507.16 676.21	0	0	7 & 28	25.5 to 59.0
Ghalehnovi et al. [47]	39	360 370 380 390 400	183.5	975	525	7	0 & 100	0 & 100	0 & 100	0 10 20 30 40	28 56 90	31.0 to 51.0

Table 1: The compiled experimental dataset.

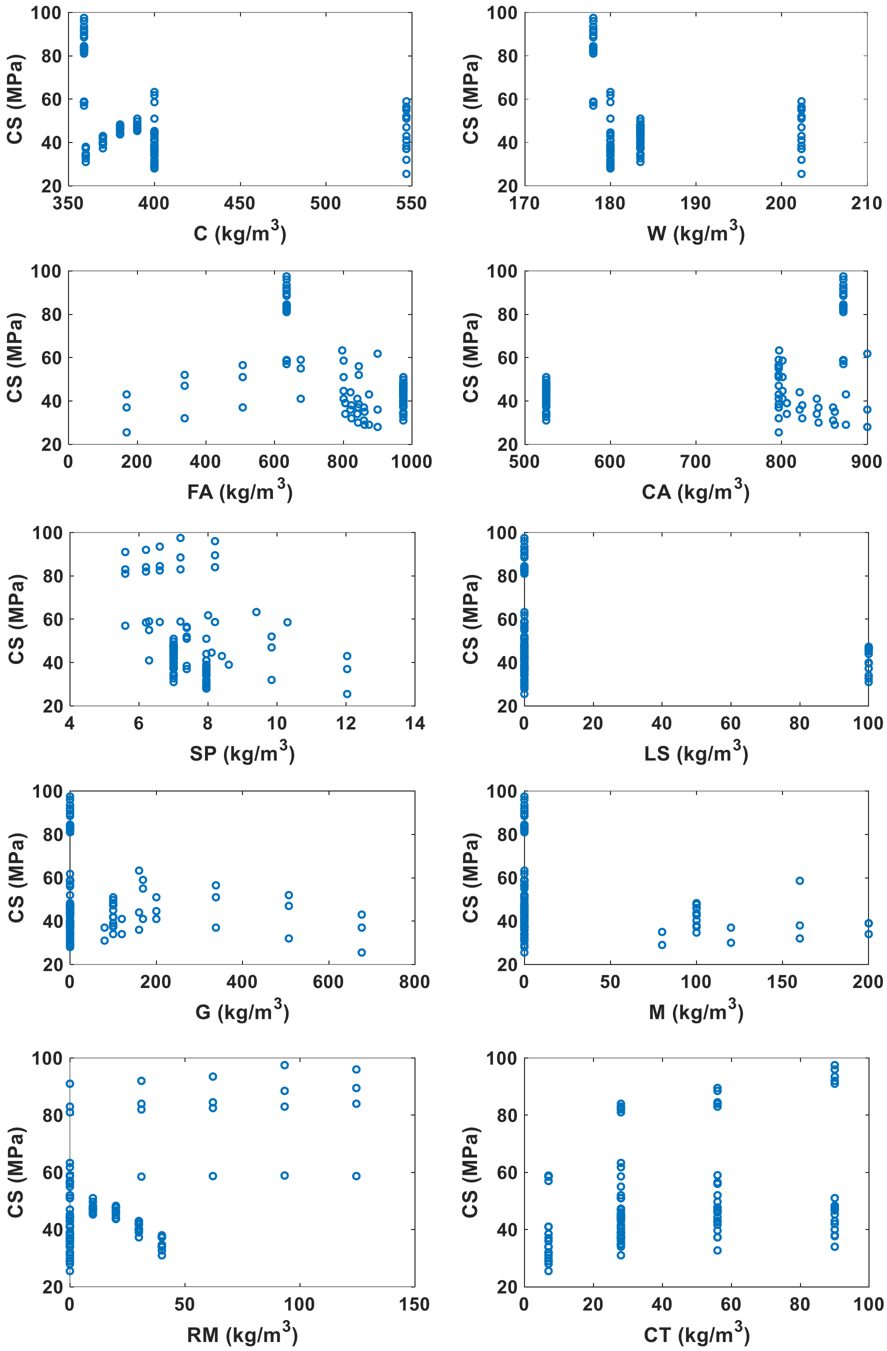

Figure 1: The distribution of CS relating to each input parameters.

3 PROPOSED ANN MODEL

To conduct the ANNs for estimating the CS of concrete specimens using waste materials, all the input and output data were normalized between 0 and 1 using their minimum and maximum values. The normalized input data is classified into training (85% of all input data) and testing (15% of all input data) sets. The training set itself is classified into 70% training and 15% validation sets. Then, the feed-forward back-propagation via the Levenberg-Marquardt algorithm was utilized for training the network. As presented in Figure 2, the ANN models' structure contained an input layer, a single hidden layer including 5 to 20 neurons and an output layer. The Tansig (tan-sigmoid) and Linear functions were selected as the transfer function in the hidden layer and the output layer, respectively. As can be seen in Figure 3, mean square error

(MSE) and correlation coefficient (R) values, respectively presented in Equations (1)-(2) are used. In addition, trial and error was employed for the hidden layer's optimal number of neurons determination.

$$R = \frac{\sum_{i=1}^{N}(Predicted_i - Predicted_{ave.})(Experimental_i - Experimental_{ave.})}{\sqrt{\sum_{i=1}^{N}(Predicted_i - Predicted_{ave.})^2(Experimental_i - Experimental_{ave.})^2}} \quad (1)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Predicted_i - Experimental_i)^2 \quad (2)$$

In Equations (1) and (2), the $Predicted_i$ and $Experimental_i$ are the estimated and measured values. The N is the data number, and the $Predicted_{ave.}$ and $Experimental_{ave.}$ are the average values of estimated and measured data. The presented results in Figure 3 indicate that the optimal of neuron numbers in the hidden layer is 11, with greater R and decreased MSE values equal to 0.9946 and 3.2111, respectively.

To calculate the estimated CS of concrete specimens including waste materials, the following equation can be utilized:

$$\mathrm{CS} = \mathrm{Linear}\left(\sum_{k=1}^{K} W_k^2 \mathrm{Tansig}\left(\sum_{i=1}^{I} W_{ki}^1 X_i + \mathrm{bias}_k^1\right) + \mathrm{bias}^2\right) \quad (3)$$

In Equation (3), I is the number of inputs (equal to 10 herein), K shows the hidden layer's neurons number (equal to 11), X_i is the input parameters, W_{ki}^1 symbolizes the linking weight between the i^{th} input layer and the hidden layer's k^{th} neuron, W_k^2 symbolizes the linking weight between k^{th} hidden layer's neuron and the independent output layer, $bias_k^1$ denotes the bias in the k^{th} hidden layer's neuron, and $bias^2$ denotes bias value in the output layer. Table 2 reports the obtained optimal biases and weights in the ANN model proposed in this study.

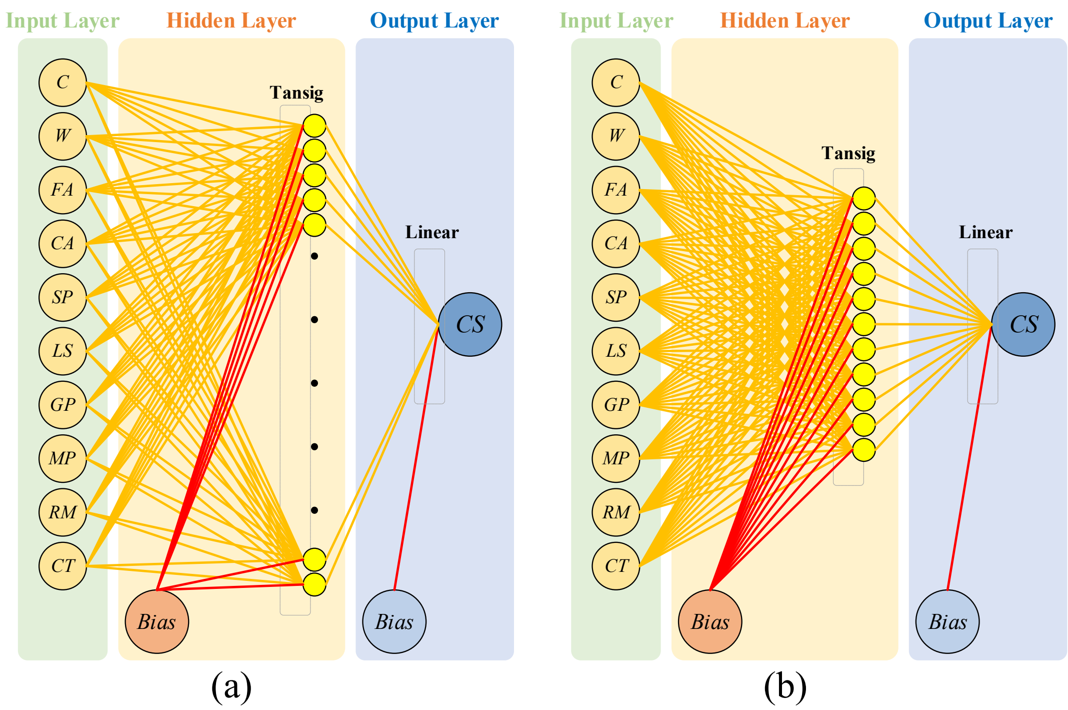

Figure 2: The proposed ANN models structure: (a) overall configuration of hidden layer with 5 to 20 neurons; (b) optimized structure.

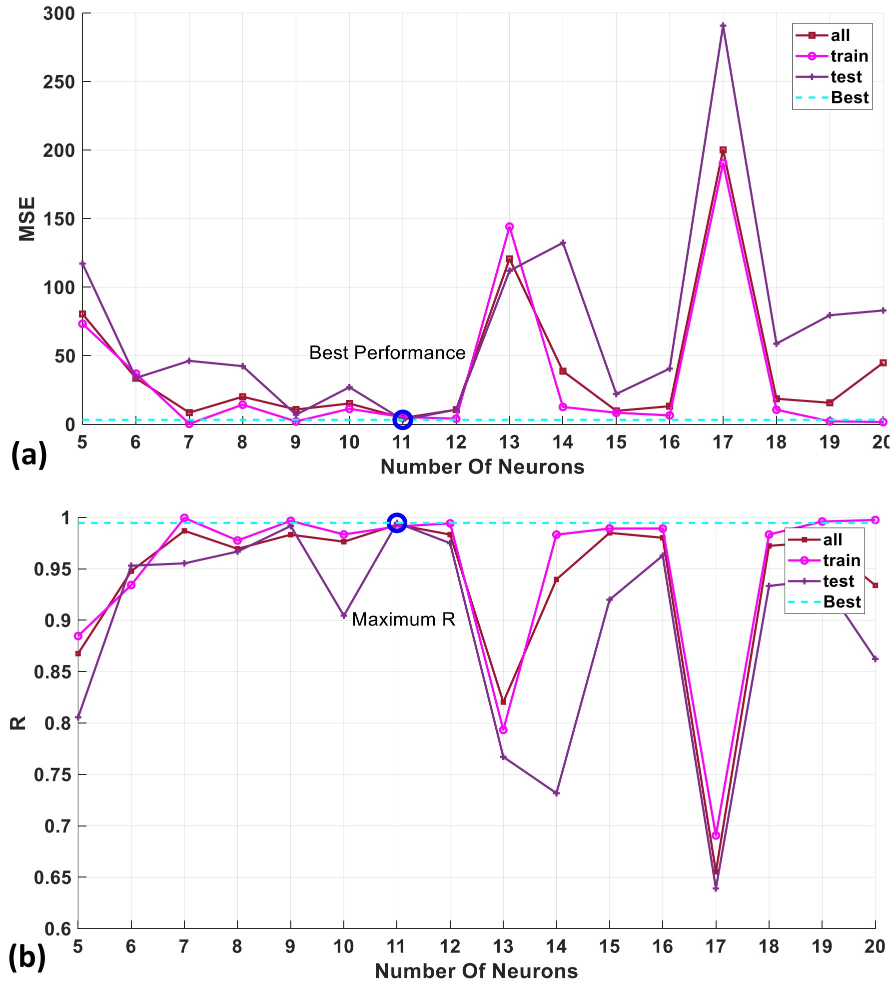

Figure 3: Selection of optimized neurons' number: (a) MSE; (b) R.

Number of neurons	Weight											Bias	
	W_{ki}^1										W_k^2		
	C	W	FA	CA	SP	LS	GP	MP	RM	CT		$bias_k^1$	$bias^2$
1	0.578	1.257	-0.353	1.444	-1.128	-0.885	0.989	-1.429	0.978	0.787	-0.445	1.042	
2	1.020	-0.856	0.984	1.655	-0.208	0.082	0.943	3.181	0.973	-4.145	-0.444	-1.077	
3	0.917	0.896	0.248	1.505	0.959	-1.336	0.184	0.453	-1.807	0.454	-0.066	1.172	
4	-0.932	-0.677	0.947	-0.681	-0.426	0.172	0.709	2.280	0.820	1.583	0.177	0.698	
5	-0.974	2.180	-0.055	-0.530	-0.270	0.354	0.737	0.360	1.411	-0.222	-1.202	0.424	
6	-0.508	0.231	0.362	-1.050	-0.670	-0.452	-1.020	0.186	0.266	0.108	-0.158	-0.080	-0.556
7	-1.000	-0.684	-0.332	0.460	-0.515	-0.558	-0.861	-0.773	-0.797	0.258	0.037	-0.037	
8	1.091	0.134	-0.526	-0.161	-0.663	-1.179	1.606	-0.846	0.266	0.272	0.885	-0.324	
9	-0.758	-0.448	-2.606	4.186	-0.793	0.428	-1.681	0.767	0.884	2.203	0.940	-2.179	
10	1.350	0.742	-0.852	-0.648	-1.575	-0.619	-0.459	0.034	0.309	0.819	-1.116	2.513	
11	0.180	0.674	0.589	0.968	0.198	0.427	0.760	1.542	-0.323	0.524	-1.043	-2.282	

Table 2: The weights and biases of the proposed ANN model.

4 ANN MODEL

To investigate the ANN model performance, the predicted vs. experimental curves, including R values in training, validation, test and all data, are presented in Figure 4. Moreover, the histogram of error values, the difference between experimental values and corresponding predicted ones, is depicted in Figure 5.

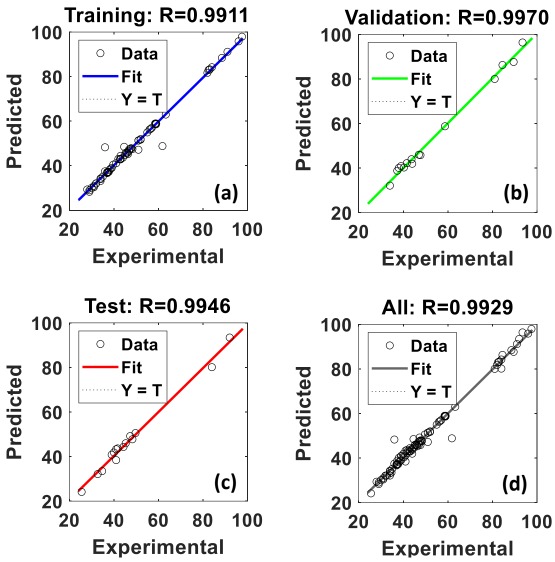

Figure 4: The predicted vs. experimental curves in the proposed ANN model for: (a) training data; (b) validation data; (c) test data; and (d) all data.

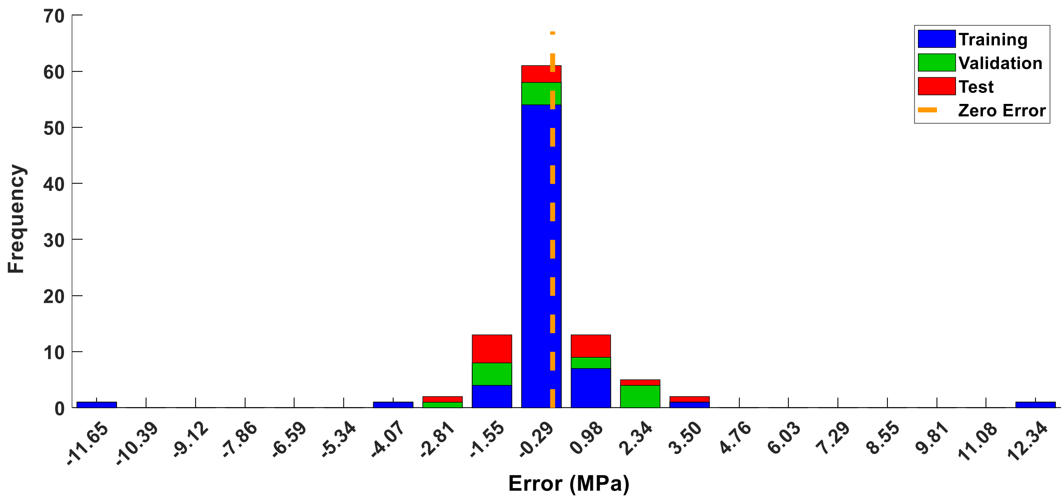

Figure 5: The ANN model's error histogram.

5 CONCLUSIONS

In the current paper, the CS of environmental-friendly concrete specimens, including various dosages of waste materials such as limestone powder (*LS*), granite powder (*GP*), marble powder (*MP*) and red mud (*RM*), was estimated by the ANN method. Moreover, the input parameters conclude of the influence of cement and water contents, fine and coarse aggregates, and the curing time was taken into consideration. To achieve this goal, a database including 99 concrete specimens was compiled, and the following results were obtained:

- Among the 5 to 20 neurons considered in the single hidden layer of proposed ANN models, the 11 neurons with R and MSE equal to 0.9946 and 3.2111 lead to the best results. Therefore, the optimal structure of the proposed ANN model was one input layer (with 10 inputs), a single hidden layer with 11 neurons, and an output layer.
- The proposed ANN model showed its perfect robustness with obtained R values of 0.99112, 0.99704, 0.99462, and 0.99290, respectively, for training, validation, test, and all data.
- The low frequencies at high error values and high frequencies at low error values admired the high accuracy of the proposed ANN model for estimating the CS of environmental-friendly concrete specimens.

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