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Artificial intelligence for the prediction of the physical and mechanical properties of a compressed earth reinforced by fibers

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Bentegri Houcine
ORCID: https://orcid.org/0009000103872950
Civil Engineering and Sustainable Development Laboratory, Faculty of Sciences and Technology, Ziane Achour University of Djelfa, 17000, Algeria
E-mail: bentegri.houcine@gmail.com , bentegri.houcine@mail.univ-djelfa.dz
Rabehi Mohamed
ORCID: https://orcid.org/000000230941720
Civil Engineering and Sustainable Development Laboratory, Faculty of Sciences and Technology, Ziane Achour University of Djelfa, 17000, Algeria
E-mail: rahmoh_moh@yahoo.fr
Kherfane Samir
ORCID: https://orcid.org/0009000462705353
Civil Engineering and Sustainable Development Laboratory, Faculty of Sciences and Technology, Ziane Achour University of Djelfa, 17000, Algeria
E-mail: sam2002mir@gmail.com
Boukansous Sarra
ORCID: https://orcid.org/000900060814661
School Of Computer Science And Information Engineering, Zhejiang Gongshan University,Hagzhou310018, China
E-mail: boukansous.sarra@gmail.com.

Abstract

The use of natural fibers as a reinforcing product in the production of compressed earth blocks can be considered as an effective means for the environment and savings. This study presents a prediction a model- and simulation-based approach using artificial neural networks (ANN) to predict tensile strength and compressive strength. of earth-friendly concrete containing different types of natural fibers. A group of data with eight influencing characteristics; cement, fiber, sand, fiber length, fiber tensile strength, clay, silt, age used for model formation and validation were collected from the literature. The output was compressive strength and tensile strength. The combination of root mean square propagation and stochastic propagation gradient descent with the momentum method is used to train the ANN. Using various validation criteria such as coefficient of determination (R), root mean squared error (RMSE) and mean absolute error (MAE), the ANN model was validated and compared to two machine learning (ML) Random Forest (RF) techniques and Multilayer Perceptron (MLP). A sensitivity analysis was also performed to validate the robustness and stability of these models. The experimental results showed that the ANN model performed better than other models and, therefore, it can be used as a suitable approach to predict the compressive strength of environmentally friendly earth concrete.

Keywords: Compressed earth block. Artificial neural networks. Fibers. Cement. Prediction.

Abbreviations: CEB, compressed earth block; ANN, artificial neural network; mean squared error (MSE), Coefficient of determination (R).

1. Introduction

Compressed earth blocks (CEB) represent a cost-effective, durable and environmentally friendly construction alternative to traditional masonry units (reinforced concrete) CEB construction includes units of local, low-cement compressed earth bricks that are quickly and efficiently fabricated on-site with local materials. CEB construction uses local soil as the main building component, which offers advantages over traditional masonry units, including efficiency and lower cost, increased energy and less environmental impact (E. Adam, 2001), and (C. Egenti et al, 2014).

Some reports in Algeria, the European Union and the United States show that a significant challenge with the prolific construction of the CEB is the lack of standardization and laws that govern this type of construction internationally (G.T.R.Allen *et al,* 2012); (H. Guillaud *et al*, 1995), (Minke.G, 2006), and (A.D.Krosnowski, 2011).

The increased development of artificial intelligence has created a faster, more efficient and less expensive tool that simulates human intelligence in solving complex problems through the application of machine learning (ML) models, which have proven to be a simpler, more efficient and effective way to predict the tensile strength and compressive strength of earth concrete compared to traditional laboratory approaches and techniques which waste time and money (A. Kandiri et al, 2020).

Currently, several ML algorithms - among which the artificial neural network (ANN) and support vector machine (SVM) models - show superb ability for prediction and generalization when used to solve multiple complex nonlinear problems (A. Zendehboudi et al, 2018). The literature has also reported that both models have been successfully used to predict the strength of earth concrete with higher accuracy and higher speed compared to other models based on regression analysis - reports by (Ahmad Shamsad et al, 2008), (H. Ling et al, 2019), (JY. Park et al, 2019), and (Taffese .W.Z et al, 2015). Various scientific works have been carried out using ML algorithms to improve the prediction of compressive and tensile strength for different types of compressed earth concrete - Reports by (M. Azimi-Pou et al, 2020), (M.S. Barkhordari et al, 2022), (R. Biswas et al, 2020), (J.-S. Chou et al, 2014), (D.Van Dao et al, 2020), (M.A.DeRousseau et al, (2019), (A. Hammoudi et al, 2019), (Q. Han et al, 2019), (M.R. Kaloop et al, 2020) and (A. Mohammed et al, 2021) and (A.-D. Pham et al, (2016) (A.-D. Pham et al, 2020), (P.F.S. Silva et al, 2020), (M. Velay-Lizancos et al, 2017), (Z.M. Yaseen et al, 2018), and (L. Zhang et al, 2019).

The mechanical properties of earth concrete structures exhibit a strong nonlinear nature derived from the parameters involved in their structure; it is this non-linear behavior that makes development and output with an analytical formula for the prediction of mechanical properties using traditional methods quite a difficult task, but with artificial intelligence, nothing is impossible.

2. Previous studies and laboratory results

Simulation and prediction models using artificial intelligence must use large and variable values and data at the same time, so that we can create models that can be incorporated and applied. Therefore, we need to ensure that the database used fulfills the conditions of abundance and change and that it is proportional and integrated and is composed of many independent variables, Because in our study it was the using eight variables as input and two variables as output (results), we expect this gives us the effectiveness of the program and its validity, and this will only be achieved if previous studies are used that serve the desired purpose (Turco C *et al*, 2021). First of all, all available information (also in text) retains the observed values. Then, only the common features of all research are considered. Table 1 quality determines the mechanical properties extracted from previous works in the literature and reinforce by laboratory studies:

Table 1 - The mechanical properties extracted from previous works in the literature and reinforce by laboratory studies

Study Ref	Type of Fiber Used	Compressive Strength	Tensile Strength	Fibers Tensile Strength
“ (Lejano B.A et al, 2019)”.	Green mussel shell and pig hair	**x**	**x**	**x**
“ (Duc Chinh Ngo et al, 2017)”.	Hemp fiber	**x**	**x**	**x**
“ (Selsiadevi .S et al, 2018)”.	Banana fibers	**x**	**x**	**x**
“ (Vodounon. N.A et al, 2018)”.	Pineapple Leaves Fibers	**x**	**x**	**x**
“ (A. Koutous et al, 2021)”.	barley straw and palm date fibers	**x**	**x**	**x**
“ (Bentegri Houcine et al, 2023)”.	Alfa fibers	**x**	**x**	**x**
This experiment	Data palm, Typha, millet waste fibers	**x**	**x**	**x**

3. Submission of used data

To train and validate the ANN model, the experimental dataset, including 188 samples, was collected from the literature. The dataset consists of eight input explanatory variables: clay (X1), sand (X2), silt (X3), cement (X4), fiber percentage (X5), fiber length (X6), strength fiber tensile (X7), age (X8).

The most important mechanical properties are that Y1 is compressive strength and tensileY2 strength is set as a response variable (output target), in order to apply the efficiency of the ANN model Table 2:

Table 2 - Statistical values of the variables (input/output)

Variables	Description Median	Min	Mean	Median	Max	Stdev	Skew
X1	Clay (%)	10	23.18	20	60	12.72	1.21
X2	Sand (%)	20	41.71	20	92	27.97	0.88
X3	Silt (%)	0	34.09	58	58	25	-0.19
X4	Fiber (%)	0	4.78	3	15	4.80	1.11
X5	Cement (%)	0	2.69	2	11	2.53	1.27
X6	Fiber length(mm)	9	23.57	9	70	18.58	1.04
X7	Fiber tensile strength(MPA)	10	924.3	766	5000	11.68	3.12
X8	Age (days)	7	20.52	21	28	8.40	-0.53
Y1	Compressive strength(MPA)	2	6.40	7	11	2.63	0.00
Y2	Tensile strength(MPA)	0.16	0.76	0.60	2.22	0.50	1.14

The initial statistical characteristics of the variables and the output target are summarized in Table 2. The training data set is used to determine the weights (or parameters) ANN of the model, which contains 188 data. To reduce fluctuations in the training ANN model, the explanatory and response variables in the dataset were scaled in the range of [0, 1].

4. Methods

4.1 Neural networks

Many successful applications for data processing and learning capabilities using ANN have been reported in the literature, Ann's basic structure consists of three layers; weighted factors, activation functions and learning functions.

The input and startup layer is a single layer containing model data and model versions. The hidden layer contains one or more layers used for data processing. In the previous layers, the neurons in these layers have positive or reverse connections between neurons, The RELU function is used as an ANN activation function.

An important factor of ANN is the optimization of the weight between neuron connections. A sentence of this weight is determined by minimizing the cost function, which is essentially a square error (MSE). The combination of intermediate square extensions and random gradient declines and pulse methods is used to determine the best value of weights, previous studies have shown that random selection of a number of hidden neurons can lead to under fitting or over fitting of the model.

A constant number of hidden layers and neurons in each layer eliminates over fitting and validates the stability of the training model. This article presents an ANN efficiency architecture model that includes three hidden layers. Experimental work was done to test all combinations using 2-30 neurons for the model in each hidden layer. The optimal number of neurons for the ANN model was determined by performing a 5-fold cross-validation using the training set. The stable ANN model includes three, eight and eleven neurons in the hidden layers, with eight neurons and one bias in the input layer and two neurons in the output layer. The architecture of the ANN model is shown in Figure 1:

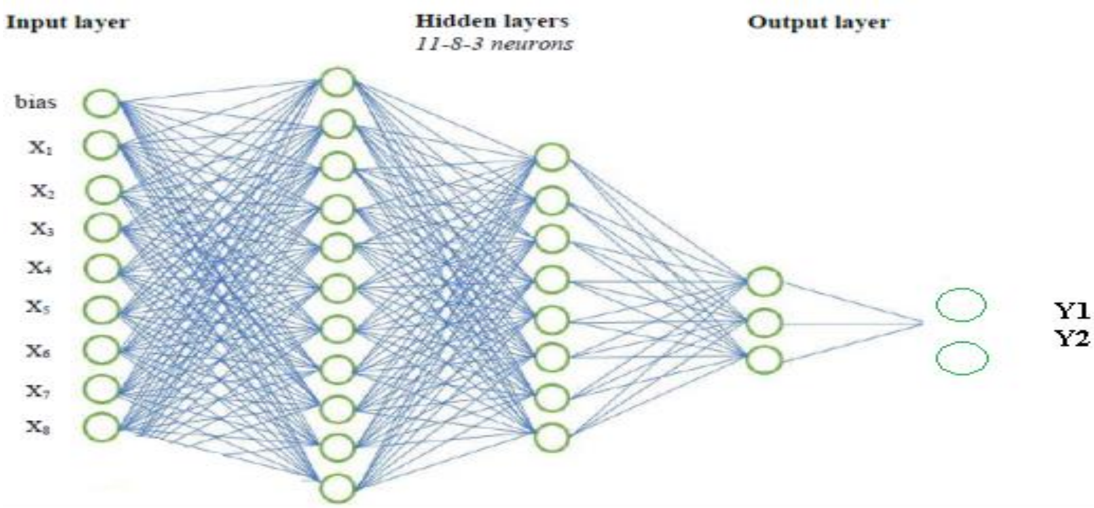

Figure 1 - Structure of the proposed ANN model: three hidden layers with eleven, eight and three hidden neurons

5. Discussion of results

5.1 Analyze the results and know the error percentage

These well-known statistical indicators, such as the coefficient of determination (R) equation (2), the squared error and the mean absolute error (MAE) were taken into account to evaluate the models of effective and predictive accuracy. The value of R shows the statistical relationship between the actual values and the predicted values of the output target (compressive and tensile strength), while MAE shows the evaluation of the error.

The performance of the created models can be assessed by evaluating the mean square error (MSE), by equation (1): Analyze the results and know the error percentage

$$MSE = \frac{1}{q}\sum_{i=n+1}^{n+q}(Y_I - Y_I)^2 \qquad (1)$$

$$R^2 = \frac{\sum_1^m (y_i - y)^2}{\sum (y_i - y)^2} \qquad (2)$$

$$RMSE = \sqrt{\frac{1}{n}\sum_{p=1}^{n}(t_I - Y_I)^2} \qquad (3)$$

5.2 Study expectations and prediction regarding compressive strength

Where (yi) and (y) are defined as the values and means of the predicted compressive or tensile strength, respectively, (Yi) and y are the values and means of the actual compressive strength, respectively; m is the number of data samples.

Artificial intelligence has proven us a high capacity and impressive results, especially in our case, where the study was carried out with neural networks, using the databases of the results of literature reinforced by laboratory studies, because it gave the output values 0.98 which is a result considered very impressive the curve of the dashed line is very close and sometimes even adjacent to the blue line and for the validation results it gave 0.92 the curve of the dashed line is very close and sometimes even adjacent to the green line which is considered very acceptable for prediction and simulation programs. And for the test results, it was given 0.97 the curve of the dashed line is very close and sometimes even adjacent to the red line, that's a very good result and incredibly close to reality. Regarding the program as a whole, the overall program interaction 0.97, and this result is considered very ideal, and the program as a whole is incredibly close to reality See Figure 4 the curve of the dashed line is very close and sometimes even adjacent to the black line.

As we notice in the statement, the dotted line represents the ideal data between the results and the forecasts, and the solid line materializes the relationship between the predicted data and the results to be achieved. It should also be noted that this program provides us with prediction possibilities and access to the knowledge of the pressure force value based only on the prediction process without the need for laboratory work experiences.

5.3 Study expectations and prediction regarding tensile strength

Analysis of the results of prediction of tensile strength formed by previous studies and reinforced by laboratory studies also showed promising results. The expected output and result values are very acceptable: 0.83 for training and practice, 0.83 for confirmation, 0.83 for testing, and 0.86 for full program validation (the MSE assessment and R) Table 3 for compressive strength and Table 4 for tensile strength).

Table 3 - Analyze (MSE and R) for compressive strength

	Observation	MSE	R
Training	133	0.8296	0.9308
Validation	28	0.3334	0.9773
Test	28	0.9080	0.8946

Table 4 - Analyze (MSE and R) for tensile strength

	Observation	MSE	R
Training	133	00427	0.8881
Validation	28	0.1301	0.8352
Test	28	0.0991	0.8344

5.4 Analyze (gradient and Mu and validation check for compressive strength and tensile strength)

So we can plot the gradient value mu and the validation fails, the purpose of the gradient is to represent the slope of the tangent to the graph of the function. It indicates the direction of high growth rate for the considered function. 'MU' is the control parameter of the back-propagation neural network we modeled, and the choice of mu directly affects the convergence of the error.

Validation checks are used to complete neural network training, the number of validation checks is directly related to the number of consecutive iterations of the neural network. The gradient for compressive strength is 0.08997 at epoch 38 and on remark Mu is 0.01 and validation checks equal to 6, which you can see in Figure 2. The gradient for tensile strength is 0.10681 at epoch 13 and on Remarque Mu are 0.001 and validation checks, equal to 6, you can see in Figure 3:

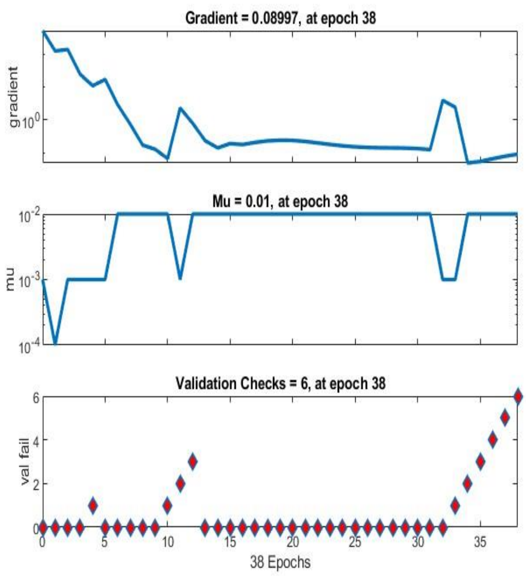

Figure 2 - Analyze (gradient and Mu and validation checks) for compressive strength

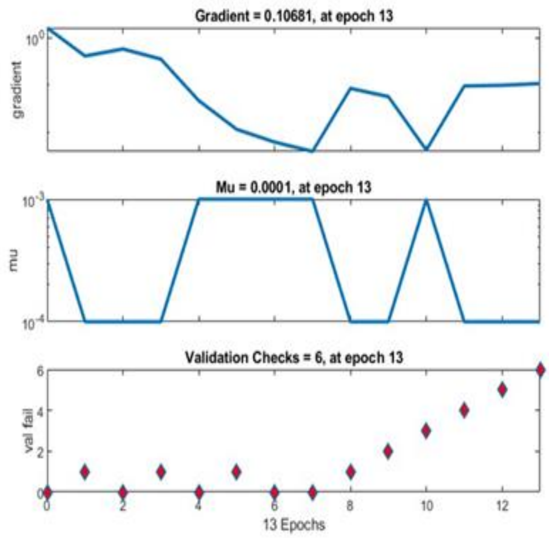

Figure 3 - Analyze (gradient and Mu and validation checks) for tensile strength

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5.5 Know the error value

5.5.1Compressive strength

The correlation coefficient found in the case of Compressive strength R = 0.98 It leaves no doubt about the effectiveness of the program Figure 4.

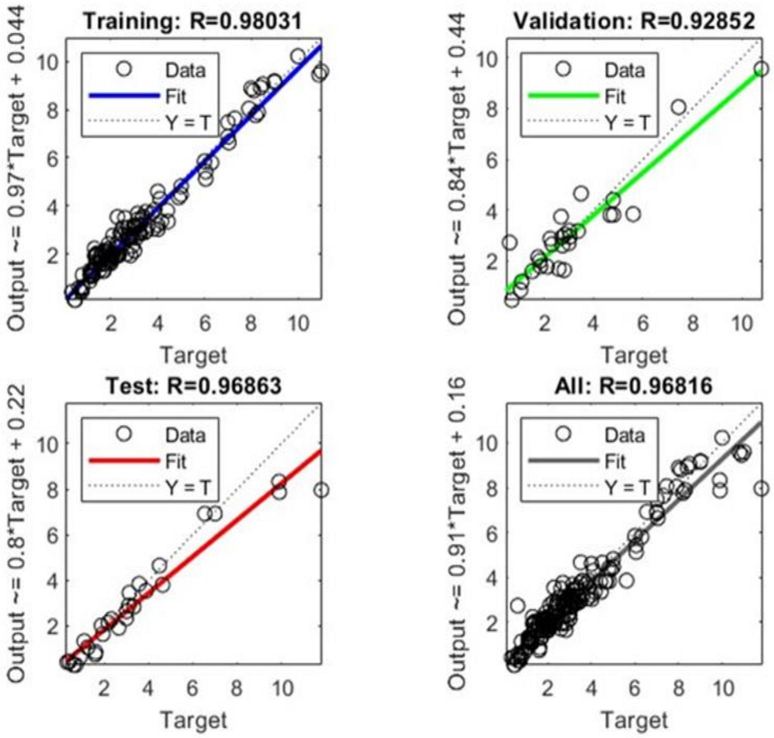

Figure 4 - Compressive strength target values and ANN actual outputs (training, validation, test, and all responses)

5.5.2 Tensile strength

The correlation coefficient of Tensile strength found in the case, of R= 0.88 again demonstrates the It leaves no doubt about the effectiveness of the program Figure5.

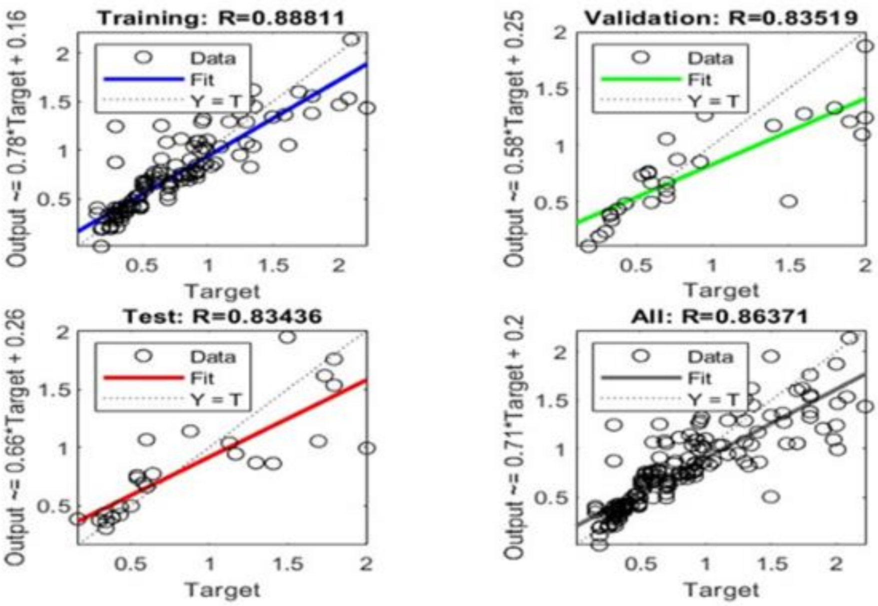

Figure5 - Tensile strength target values and ANN actual outputs (training, validation, test, and all responses)

Unlike the MSE (Equation (1)), the MSE formula does not have a square root; hence, the error can also assume negative values. The graphs of Figure 6 indicate at which iteration (epoch) the validation phase reaches the lowest MSE value, the best performance. The convergence occurs at epoch 32, with the MSE equal to 0.61519 for compressive strength, and epoch 7, with the MSE equal to 0.13012 for tensile strength. The figures also confirm that the ANN models are working correctly since the MSE trend of the training set is lower than those of the validation and testing sets, which are reasonably similar.

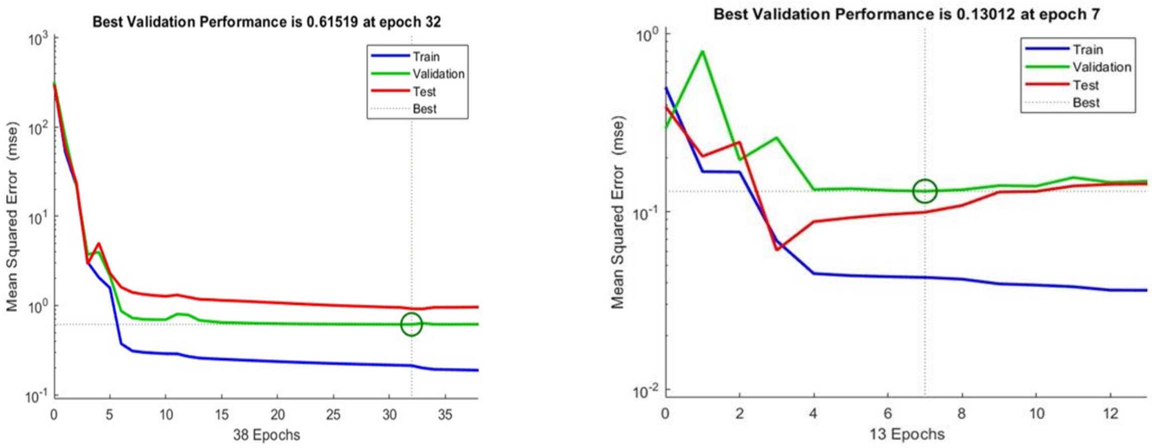

Figure 6 - Best validation Performance of the trained networks: (a) compressive strength left and (b) tensile strength right

5.6 Error histograms for compressive strength and tensile strength

The error histograms are shown in Figure 7. The error ranges from -1.97 to 3.689 for compressive strength and -0.896 to 0.9656 for tensile strength. Analyzing the first (Figure 7a), the outliers at the extreme sides of the graph are negligible. Most of the data used for training, validation, and model tests are centered on the histogram, near the zero error line. In the case of Figure 7b, the errors are, on the contrary, more widely distributed in the interval. However, it should be noted that, in proportion to the values taken by the tensile strength, the corresponding error values are acceptable.

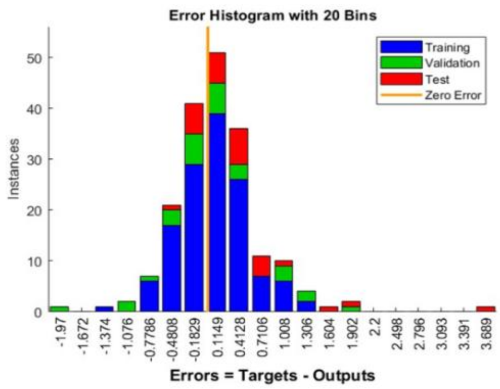

Figure - 7a Error histograms for compressive strength

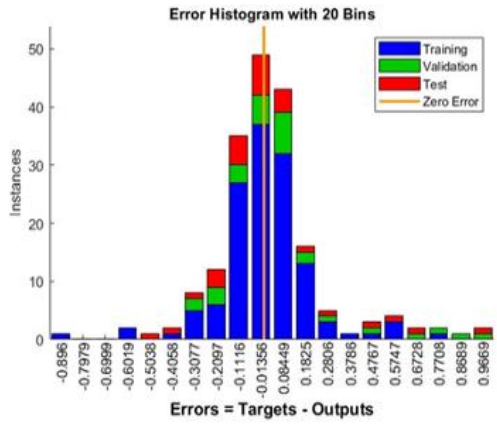

Figure -7b Error histograms tensile strength

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6.Conclusions

This study investigates the application of network (ANN) models for the prediction of tensile strength and compressive of earth concrete blocks. The comparison between derived and experimental results clearly demonstrates the efficiency and speed of ANNs in building a series of soft sensors to reliably and comprehensively predict their compressive and tensile strength.

In this study, the three-layer hidden ANN model was proposed and compared with two machine learning techniques, which are Random Forest and Multilayer Perceptron, to expect the tensile strength and compressive of earth concrete with natural fiber.

A dataset comprising 188 samples was collected from the literature and used for modeling. Validation of the models was carried out using statistical indicators such as RMSE, MAE and R. The ANN model archived the highest R value of 0.9773 and the lowest MSE value was 0. 8344 respectively of the whole of the testing, a sensitivity analysis with 200 simulations was carried out to validate these models.

The results showed that the ANN was more robust and stable than the other models and can be considered as a suitable approach to predict compressive and tensile strength.

But we lack regulations and laws that determine how to build this type of material despite numerous studies being carried out, because so far there are no laws or regulations agreed internationally. This is what we as researchers seek to achieve with the help of artificial intelligence.

ANNs can provide reliable solutions when used in CEB optimization to guide campaigns and support digital surveys and create a foundation for dating regular executives the possibility of carrying out several mixtures of different character with a limited time and opens up the possibility for the researcher to make new concrete that respects the environment.

The accuracy of network predictions depends on the quality of data used, and it would be it is in your interest to enrich it if new variables are added. For this purpose, the data entered into the study (fiber, cement, etc.) and the output data are changed with decrease or increase depending on the objective of the study and the results to be achieved.

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