

Strength prediction of mortar reinforced with babassu coconut fiber using artificial neural networks

Previsão de resistência de argamassa reforçada com fibra de coco babaçu usando redes neurais artificiais

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Abstract

Using natural fibers as reinforcement in cement composites is a sustainable alternative in the construction industry. Nevertheless, the dosage of these materials employing traditional methods depends on laboratory tests and tends to be laborious and expensive. Thus, predicting composites characteristics can save time and reduce operating costs. In this study, Artificial Neural Networks (ANN) trained with Extreme Learning Machine (ELM) were used to predict the tensile and compressive strengths of mortar reinforced with babassu coconut fiber. Babassu coconut is an abundant product in the region where this research was carried out, and its use tends to bring socio-economic benefits. The data was obtained experimentally, generating a total of 51 samples. The ANN topologies have six parameters in the input layer (cement, sand, water/cement ratio, maximum fiber length, fiber percentage, and slump), one parameter in the output layer (tensile or compressive strength), and one hidden layer, which contains 6 and 7 neurons, respectively, in the tensile (ELM-T) and compressive (ELM-C) strength prediction models. Simulation results indicated that both models are promising tools for predicting the mechanical behavior of mortars reinforced with babassu coconut fibers.

Keywords: Fiber-reinforced mortar. Babassu coconut fiber. Artificial neural networks. Strength prediction.

Resumo

A utilização de fibras vegetais como reforço em compósitos cimentícios é uma alternativa sustentável na construção civil. Entretanto, a dosagem desses materiais pelos métodos tradicionais depende de ensaios laboratoriais e tende a ser trabalhosa e cara. Assim, a previsão de características de compósitos pode proporcionar economia de tempo e redução de custos operacionais. Neste estudo, Redes Neurais Artificiais (RNA) treinadas com máquina de aprendizagem extrema (ELM) foram utilizadas para prever as resistências à tração e à compressão de argamassa reforçada com fibra de coco babaçu, produto abundante na região onde esta pesquisa foi desenvolvida e cuja utilização tende a trazer benefícios socioeconômicos. Os dados foram obtidos experimentalmente totalizando 51 amostras. As topologias de RNA adotadas possuem seis parâmetros na camada entrada (cimento, areia, relação água/cimento, comprimento máximo da fibra, percentual de fibra e abatimento), um parâmetro na camada de saída (resistência à tração ou à compressão) e uma camada oculta, que possui 6 e 7 neurônios, respectivamente, nos modelos de previsão de resistência à tração (ELM-T) e à compressão (ELM-C). Os resultados das simulações indicaram que ambos os modelos são ferramentas promissoras para previsão do comportamento mecânico de argamassa reforçada com fibra de coco babaçu.

Palavras-chave: Argamassa reforçada com fibras. Fibras do coco babaçu. Redes neurais artificiais. Previsão de resistências.

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Introduction

The construction industry is a sector known for its substantial consumption of natural resources. Consequently, the adoption of materials sourced from renewable sources becomes crucial to maintaining a sustainable supply of raw materials in this context (Dalvi, 2014). Simultaneously, there is an ongoing effort to explore and implement innovative technologies that can enhance the quality of materials used, including the utilization of composites (Ventura, 2009).

Composites are formed by the combination of two or more materials with different physical and chemical properties, aiming to obtain a new material that exhibits characteristics not observed individually in the constituent elements, thereby achieving improved performance (Callister Junior; Rethwisch, 2016).

Due to their superior characteristics regarding strength, the most significant composites are those reinforced by fibers (Callister Junior; Rethwisch, 2016). The fibers withstand the stresses transmitted by the matrix material, which in turn shields them from circumstances that could degrade their mechanical properties (Askeland; Wringht, 2015).

Choosing natural fibers as reinforcement in composite fabrication offers several advantage. Souza *et al.* (2017) highlight, for instance, that the vast variability of woody and fibrous plants enhances the potential for discovering natural fibers with desired properties. Furthermore, fibers are highly available once they are renewable materials.

As Brazil has great potential for obtaining natural fibers, given its extensive cultivable territory and vegetation diversity, using this material as reinforcement in cementitious materials is a possibility that aligns with the need to use renewable materials.

The babassu palm is widespread across various regions of Brazil, including Maranhão and Pará, the locations where the current research was conducted. This palm tree holds significant socio-environmental and economic importance, serving as a livelihood for the communities of coconut breakers in regions with higher incidence of the species. Additionally, numerous projects involving coconut breaker organizations and the babassu production chain aim to support these communities through the construction and adaptation of facilities for processing, development of new production techniques, equipment, and new products, among other initiatives (Silva; Napolitano; Bastos, 2016).

Therefore, considering the babassu coconut, the fruit of this palm tree, as an alternative for extracting renewable material and recognizing that the utilization of parts of this material could benefit the communities of coconut breakers, it was chosen to use fibers from the babassu coconut epicarp as reinforcement for the material produced in the present study.

The babassu coconut epicarp, also known by coconut breakers as "coconut chapel" is the outermost part of the fruit characterized by its tough, fibrous texture. In addition to its use in handicrafts and its contribution to charcoal production (in conjunction with other parts of the coconut) (Carrazza; Ávila; Silva, 2012), various studies have explored the use of this material, such as in the manufacture of adobe (Amaral, 2017) and soil-cement bricks (Carvalho, 2019), in the manufacture of particleboards (Dias *et al.*, 2017; Machado *et al.*, 2017a, 2017b) and as reinforcement in polymeric matrices (Almeida, 2019; Fonteles; Alves; Barbosa, 2013; Franco, 2010; Reul; Carvalho; Canedo, 2018; Rodrigues, 2019) and cementitious matrices (Dourado, 2019; Ribeiro; Quintanilha, 2016).

Verification of the estimated characteristics and strengths of composites is subject to dosage using the traditional method and depends on laboratory tests to validate this process. These experimental tests are standardized and have well-defined processes. However, these techniques tend to be laborious and expensive and they usually require adjustments by trial and error (Muro, 2022). Therefore, developing a reliable model for predicting these composites characteristics can save time and reduce operating costs (Hamidian *et al.*, 2022).

The literature shows that several studies were developed to predict the mechanical behavior of concrete and mortar using Artificial Intelligence (AI) (Nunez *et al.*, 2021). Concerning fiber-reinforced composites, it is possible to mention the use of AI techniques to predict mechanical behavior, such as tensile and compressive strengths, when using steel fibers (Afshoon; Miri; Mousavi, 2023; Cai *et al.*, 2022; Kavya *et al.*, 2022; Silva *et al.*, 2022), glass fibers (Stel'Makh *et al.*, 2022), polypropylene fibers (Li; Song, 2022), basalt fibers (Hasanzadeh *et al.*, 2022) and natural fibers (Kumar; Vasugi, 2022; Li *et al.*, 2022).

Among the various AI techniques used to predict mechanical behavior, Artificial Neural Networks (ANN) stand out for simulating the behavior of the human brain. Thus, this technique has powerful characteristics in

information knowing and processing (Ince, 2004). In recent years, several studies have investigated the potential use of ANNs to predict concrete and mortar characteristics, such as compressive strength (Armaghani; Asteris, 2021; Pazouki; Pourghorban, 2022), tensile strength (Abellán-García *et al.*, 2022; Kim; Oh, 2021), flexural strength (Boumaaza *et al.*, 2022; Huang *et al.*, 2021) and toughness (Congro *et al.*, 2023).

An ANN is made up of several neurons grouped into layers, which can be input, hidden, or output. The number of layers of an ANN and the respective number of neurons form its topology. All neurons in a layer are connected to the next layer, but there is no connection between neurons in the same layer. This connection is made through the inputs and outputs of the neuron (Qu; Cai; Chang, 2018). Each neuron can have one or more inputs and only one output. The values present in the neuron's inputs are multiplied by the corresponding weights and the product is then added and applied to an activation function to generate the output value (Alshihri; Azmy; El-Bisy, 2009).

The prediction made by the ANN depends on adjusting the weights of each neuron in a process called training. Among the various training algorithms available, the Extreme Learning Machine (ELM) stands out, which is applicable to single-hidden layer neural networks (Al-Shamiri *et al.*, 2019). During ELM training, the hidden layer weights are chosen randomly and the output layer weights are determined analytically, without the need for the iterative cycles typical of conventional training algorithms. As a result, ELM provides ANNs with good generalization performance associated with fast learning speed (Huang; Zhu; Siew, 2004).

In view of the above, in this study, fibers from the babassu coconut epicarp were used as reinforcement in cement mortar to verify the tensile and compressive strengths. In addition, using the experimental data, models based on Artificial Neural Networks (ANNs) trained with Extreme Learning Machine (ELM) were implemented to predict the observed strengths.

Materials and methods

Experimental procedure

Materials used

The cement used was Portland CP IV-32 by Poty, with a specific mass of 2.91 g/cm³ determined by NBR 16605 (ABNT, 2017). The water used in all the mixtures was obtained from the local supply network of São Luís, the capital city of Maranhão, a northeastern Brazilian state. The fine aggregate used was natural sand. The specific mass and water absorption tests were carried out following NBR 16916 (ABNT, 2021). The values of 1.86 g/cm³, 1.96 g/cm³, and 2.07 g/cm³, were found for the specific mass of the dry aggregate, the specific mass of the saturated dry aggregate, and the specific mass, respectively. As for water absorption, a percentage of 5.49% was obtained. From the granulometry analysis, carried out per NBR 17054 (ABNT, 2022), it was possible to obtain the fineness module and maximum particle diameter as being 2.043 mm and 4.75 mm, respectively.

The fibers come from babassu coconuts harvested in the Vale do Pindaré region, Maranhão, which were sent to the Artesanato Tukayana Coconut, a group of artisans located in Lago da Pedra, a city of Maranhão, which made use of the other parts of the coconut enabling the extraction of the epicarp.

To obtain the fiber, the method presented by Amaral (2017) was used. The babassu coconut epicarp was processed in a 1.5 hp Cid forage crusher equipped with two blades, two hammers, and a 12 mm sieve. The fibers obtained in this process were sieved for a brief separation of the material and divided into two types (Table 1), which can be seen in Figure 1.

Table 1 - Types of fibers and their respective diameters and maximum lengths

Type	Maximum diameter	Maximum length
Fb1	2.00 mm	34 mm
Fb2	2.36 mm	73 mm

Figure 1 - Fb1 and Fb2 fibers



The specific masses of the fibers were obtained from an adaptation of the test for determining the density and water absorption of fine aggregate, established by the NBR 16916 (ABNT, 2021). Adaptations occurred in three steps:

- in the preparation of the sample, where they remained covered with water until mass constancy in their saturated state;
- during sample preparation, when the material was drying, it was only visually verified that the fibers were not adhered to each other; and
- the quantity of material subjected to the test. The standard recommends that 500 g of material should be submitted for each procedure. However, as the fibers form a very bulky material, 50 g of fiber was used in each stage.

From the procedures, it was possible to obtain Table 2.

Production of test specimens

The mixture used to product the batches was in a mass ratio of 1:3 (cement:sand) in cylindrical molds measuring 50 mm in diameter and 100 mm in height. The batches varied in the fiber reinforcement inserted (0, 1%, and 2% in relation to the mortar volume), the water/cement ratio adopted (0.45, 0.59 and 0.61), and the type of fiber used (Fb1 and Fb2).

The mixtures were prepared in a 5 L mortar mixer. Once the mortar was ready, the batches were subjected to the slump test to determine the consistency index and then molded; both procedures were carried out following NBR 7215 (ABNT, 2019). The specimens were kept in the molds for 24 hours. Once they were unmolded, specimens were identified, weighed, and immersed in water for curing. At 28 days, samples were subjected to compressive and tensile strength tests, under NBR 7215 (ABNT, 2019) and NBR 7222 (ABNT, 2011), respectively. Variations in batches, and the results of tests can be seen in Table 3.

Based on the consistency indices presented in Table 3, it was observed that batches with higher values in this index correspond to those with a higher water/cement ratio. Moreover, increasing the percentage of fiber added to the matrix decreases the composite's consistency index, which can be attributed to the high water absorption of the fiber. Additionally, that composites utilizing Fb1 fibers exhibited lower indices compared to those utilizing Fb2 fibers. This is due to the smaller size of Fb1 fibers compared to Fb2 fibers; hence, owing to the increased surface area, smaller fibers absorb water more rapidly than larger ones.

The presence of fibers in the composites decreased both compression and tensile strengths compared to reference mortars. This can be explained by the high water absorption and consequent volume variation of the fibers, thus generating an increase in the void index inside the specimens. Conversely, the use of water-blocking and water-repellent agents as treatment for natural fibers used in cement composites can enhance the durability of the composite (Souza *et al.*, 2017), as well as improve the volumetric stability of the fibers and the transfer of stress between fiber and matrix (Fidelis, 2014). Regarding specifically the fibers from babassu coconut epicarp, Dourado (2019) used an alkaline treatment based on sodium hydroxide (NaOH) and obtained superior results compared to untreated fibers. Therefore, it is estimated that appropriate treatment of the fiber type used in this study tends to improve the mechanical properties of mortars.

Table 2 - Characteristics of the fibers from babassu coconut epicarp

Specific mass of dry aggregate (g/cm ³)	Specific mass of saturated dry aggregate (g/cm ³)	Specific mass (g/cm ³)	Water absorption
0.67	1.22	1.49	82.77%

Table 3 - Test results

Type of fiber	Percentage of fiber	W/C ratio	Consistency index	Tensile strength (MPa)	Standard deviation	Compressive strength (MPa)	Standard deviation
-	0	0.61	276	4.405	0.545	22.514	2.768
Fb1	1%	0.61	261	3.165	0.451	16.149	2.160
Fb1	2%	0.61	258	3.191	0.116	16.603	0.745
Fb2	1%	0.61	274	3.754	0.185	17.627	2.171
Fb2	2%	0.61	263	2.886	0.295	16.396	1.757
-	0%	0.45	236	4.957	0.581	14.812	2.448
Fb1	2%	0.45	173.3	4.345	0.254	21.318	1.012
Fb2	2%	0.45	218.1	3.597	0.236	17.539	1.377
-	0%	0.59	247.5	4.441	0.313	20.050	0.670
Fb1	1%	0.59	222.5	3.588	0.314	18.650	0.625
Fb1	2%	0.59	212.5	3.094	0.201	17.087	0.246
Fb2	1%	0.59	227.5	3.645	0.326	16.658	0.815
Fb2	2%	0.59	222.5	3.272	0.210	18.001	2.430

However, it was observed that the specimens of the reference mortars exhibit significantly higher deformation than the fiber-reinforced specimens when subjected to tensile failure, which can be seen in Figure 2. In other words, despite the reduction in strengths, the use of this type of reinforcement under the conditions presented in this study is advantageous in applications where increased toughness and greater impact resistance are desired.

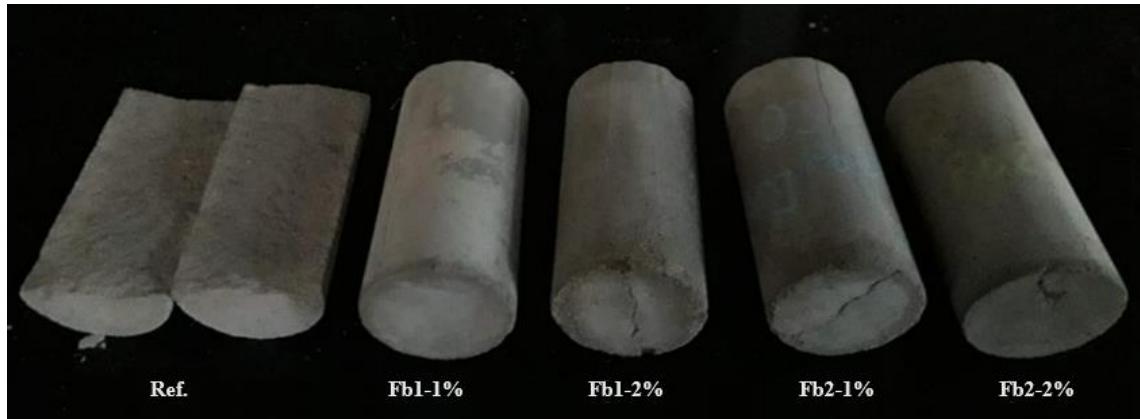
Database

In this study, the database used to implement the models contains 51 samples, which come from the tests carried out on the 13 batches produced in the experimental stage (Table 3). Although there aren't very many samples, this quantity is sufficient to prevent the dataset from being classified as small samples, which are datasets where the number of samples is less than 30 (Chen *et al.*, 2017). Additionally, the ELM algorithm, which will be used to train the neural networks in this study, exhibits nonlinear information processing ability (Ding *et al.*, 2015), enabling its application with satisfactory results even in problems with small samples datasets (Akusok *et al.*, 2015; Huang *et al.*, 2012; Pan *et al.*, 2020). It is also worth noting that it is not uncommon to have studies aimed at predicting the mechanical properties of cement composites using neural networks trained from reduced experimental databases (Clemente; Alimorong; Concha, 2019; Gifto; Gopal, 2021; Hodhod; Abdeen, 2011; Kumar; Rajasekhar, 2017; Kumar; Vasugi, 2022; Shao *et al.*, 2023; Soniya; Chithra, 2022).

The general table with the complete database is available in the Mendeley Data repository¹. The data in this table was randomly separated to generate the training and test sets. The training set contains 80% of the samples, while the testing set contains the remaining 20%.

¹Database link: <http://doi.org/10.17632/p2j6psch8r.1>

Figure 2 - Specimens after tensile failure by diametrical compression



Before implementing the models, the data set must undergo normalization. This prevents differences in data units and magnitude scales from affecting the results of models (Guo *et al.*, 2021; Liu *et al.*, 2020). The method used in this study was min-max normalization, which normalizes the real data in a range from 0 to 1 using Equation 1. After the data was applied to implement the models, a denormalization process (Equation 2) was conducted to return the normalized data values to their real values based on the prediction results.

$$x'_r = \frac{x_r - x_{min}}{x_{max} - x_{min}} \quad \text{Eq. 1}$$

$$x_r = x'_r(x_{max} - x_{min}) + x_{min} \quad \text{Eq. 2}$$

Where:

x'_r is normalized data;

x_r is actual data; and

x_{min} , x_{max} are minimum and maximum data values, respectively.

ANN topology

The ANN topology used in this study consists of three layers: an input layer, a hidden layer, and an output layer. The input layer has 6 neurons, which represent the input variables: cement, sand, water/cement ratio, maximum fiber length, fiber percentage, and slump, as shown in the database. The output layer has only one neuron, representing the required strength (tensile or compressive). The hidden layer has neurons that use the sigmoid activation function. However, defining the ideal number of hidden neurons is not a trivial task, as using an inadequate number of neurons can lead to poor performance of the ANN. On the one hand, a large number can result in a model that has excellent accuracy on training data but fails on test data. On the other hand, when the number of hidden neurons is too small, there will be a fitting problem, in which the model will not be able to learn the relationships in the training data or generalize to new data (Al-Shamiri *et al.*, 2019).

In this sense, to establish the number of hidden neurons (n), it was decided to compare heuristic rules commonly used for this purpose, which take into account the number of neurons present in the input layer (e) and the output layer (s) (Ponte, 2020; Silva; Spatti; Flauzino, 2010). The heuristic rules chosen, their equations, and the number of neurons indicated by each one, can be seen in Table 4.

Knowing that each rule indicates a different topology, the k -fold cross-validation method was used to compare the indicated topologies and, consequently, select the best rule. In this method, the training data is divided equally into k groups, one of which is chosen as the validation group, and the others are used as the training group. The learning process is repeated k times and each group is used exactly once for validation (Rathakrishnan; Beddu; Ahmed, 2022; Sultana *et al.*, 2020). The performance of a given topology in each of the k repetitions was calculated using the root mean square error (RMSE). In this way, the general performance of this topology can be calculated through the average of the RMSE values obtained in each of the k learning cycles, according to Equation 3.

$$D = \frac{1}{k} \sum_{i=1}^k d_i \quad \text{Eq. 3}$$

Where:

D is overall performance of the topology in the k -fold cross-validation process; and

d_i : is performance of the topology in the i -th learning cycle.

As ELM training initializes the hidden layer weights randomly and keeps them fixed, the cross-validation process was repeated 50 times with all topologies in Table 4, with the lowest value of D obtained in all repetitions being considered as the overall performance of each one of them.

In addition, to verify any possible influence of the number of partitions on the performance of the topologies, this study analyzed four cross-validation scenarios, adopting values of 4, 5, 8, and 10 for k .

The results of applying cross-validation to the topologies indicated in Table 4 for tensile strength and compressive strength are shown in Figures 3 and 4, respectively.

Figures 3 and 4 show that the most promising numbers of hidden neurons for networks designed to predict tensile and compressive strengths are 6 and 7, respectively, which correspond to values within the range determined by the Fletcher-Gloss rule, regardless of the value chosen for k . That being said, the network topologies that were used to implement the prediction models in this study can be seen in Figures 5 and 6. These topologies were trained using all the data contained in the training subset, as indicated in the section discussing the database, generating the tensile strength (ELM-T) and compressive strength (ELM-C) prediction models. To achieve this, the training process was carried out 50 times using ELM, and the model with the best performance was adopted, taking into account the RMSE calculated on the test data.

Results and discussion

Once the ELM-T and ELM-C models had been obtained for predicting tensile and compressive strengths, respectively, some performance indicators were applied to check their predictive capacity, taking test data as a reference. These prediction results can be seen in Figures 7 and 8.

Table 4 - Heuristic rules for determining the number of hidden neurons

Rule	Equation	Number of hidden neurons (topology)
Average value rule	$n = (e + s)/2$	4
Square root rule	$n = \sqrt{e \cdot p}$	2
Kolmogorov rule	$n = 2e + 1$	13
Fletcher-Gloss rule	$2\sqrt{e} + s \leq n \leq 2e + 1$	$6 \leq n \leq 13$

Figure 3 - Performance of topologies in cross-validation for tensile strength

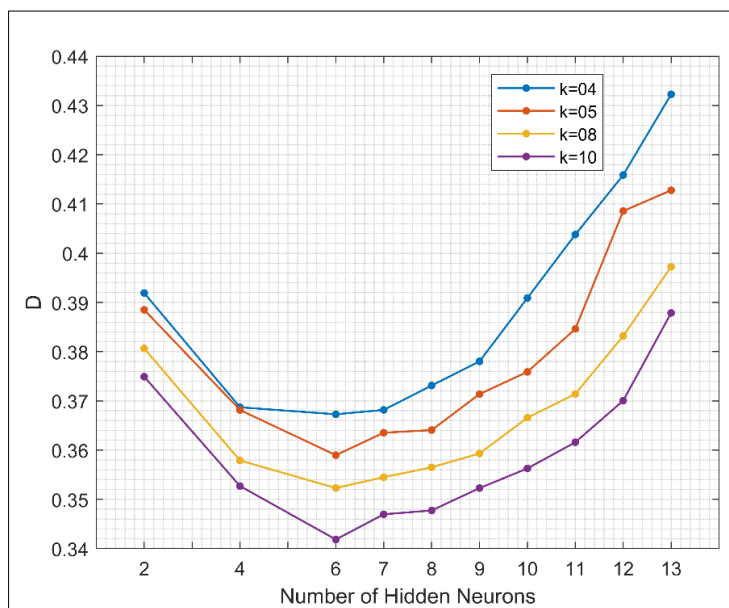


Figure 4 - Performance of topologies in cross-validation for compressive strength

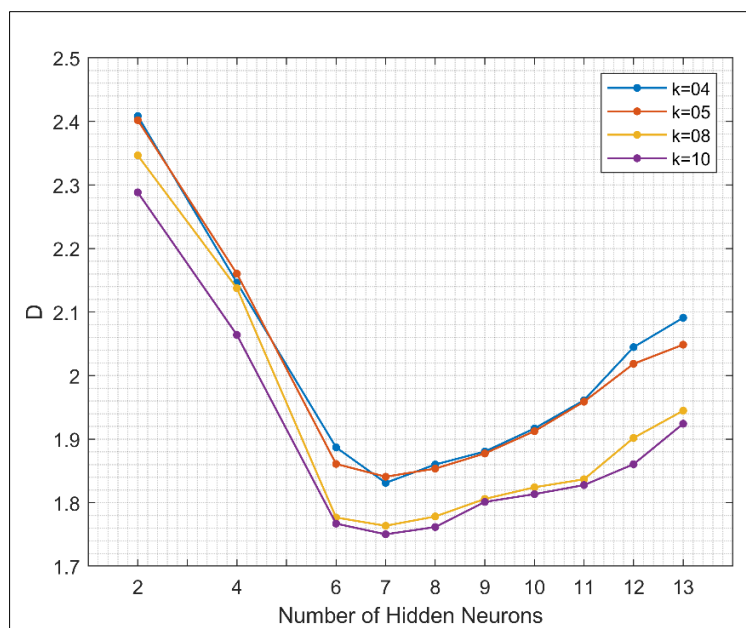


Figure 5 - ANN topology for the tensile strength prediction model

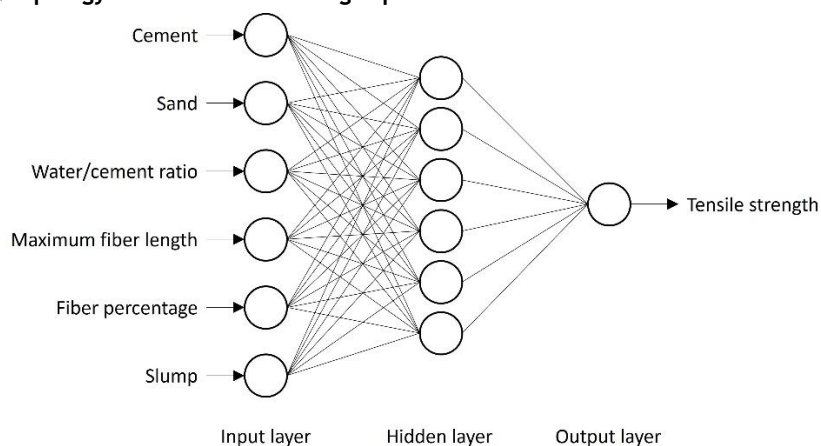


Figure 6 - ANN topology for the compressive strength prediction model

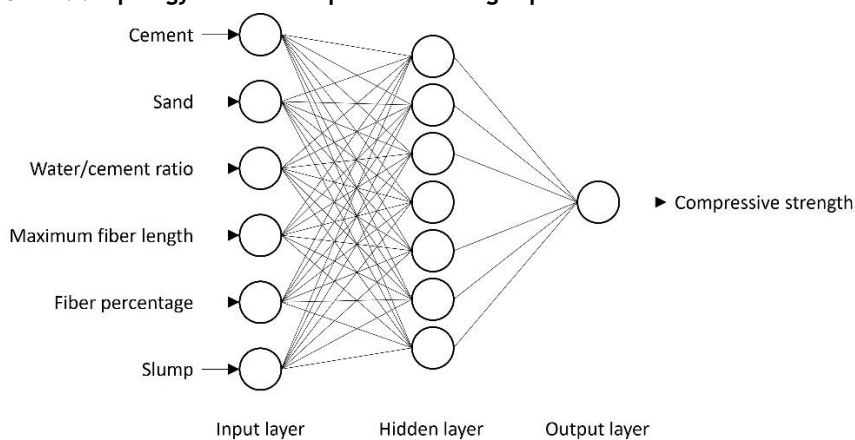


Figure 7 - Tensile strength results

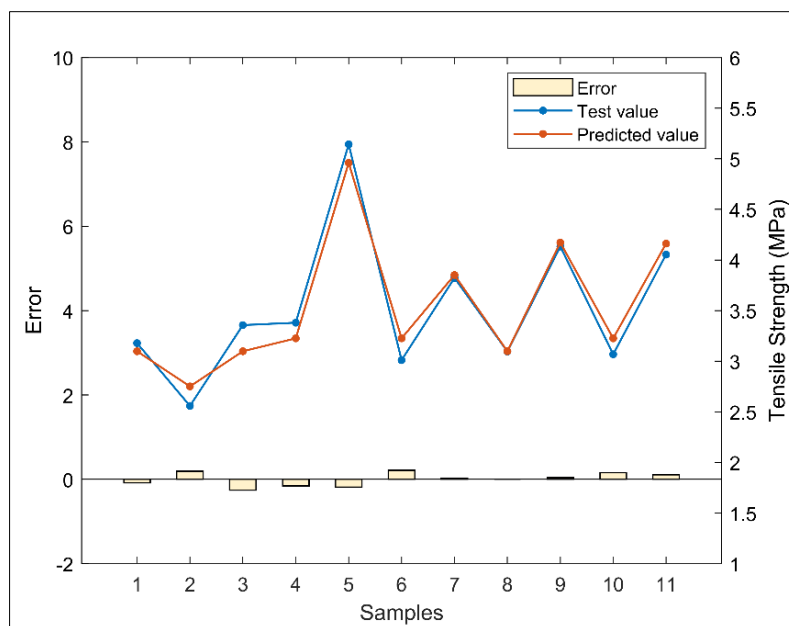
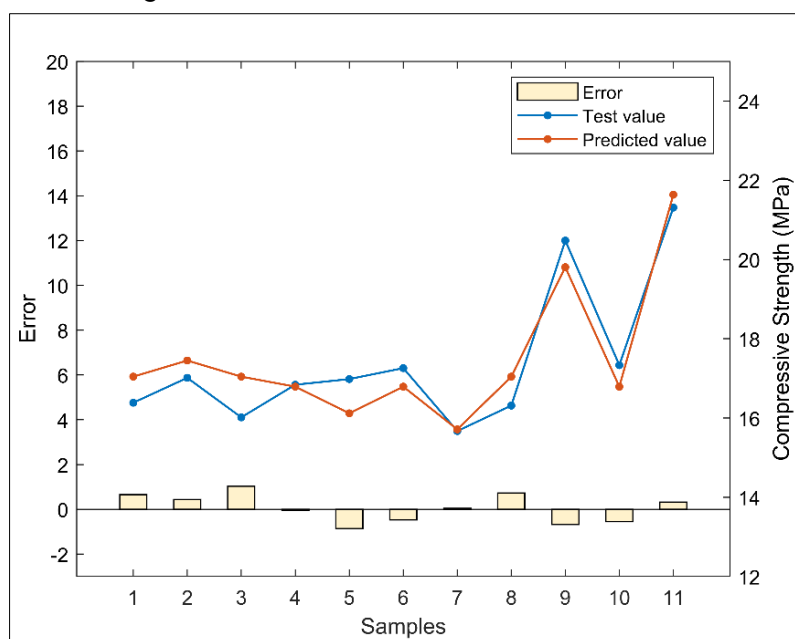


Figure 8 - Compressive strength results



Figures 7 and 8 present the actual and predicted values of the 11 samples contained in the test subset, as well as the respective absolute errors. The statistical data for these errors and also for the relative errors can be seen in Table 5. It can be seen that the maximum absolute error was less than 1 MPa for predicting tensile strength. This variation appears to be very small and can occur within the same batch. Thus, it indicates good predictability of the ELM-T model. The absolute minimum and maximum errors presented by the ELM-C model were 0.0423 MPa and 1.027 MPa, respectively. Considering the magnitude of the results, these errors are very small and within the limits of variations commonly observed in the same batch. It can therefore be said that the ELM-C model performed satisfactorily.

It is worth noting that the data presented in Figures 6 and 7 were randomly selected to compose the test set and were not used by the models during the training. Nevertheless, these data were predicted satisfactorily, despite the models not being trained on a significant amount of data.

Figures 9 and 10 show the correlation between the actual and predicted tensile and compressive strengths, respectively. In both it can be seen that the points are between -10% and +10% of the identity line with a coefficient of determination (R^2) equal to 0.9506 for tensile strength and equal to 0.8760 for compressive strength.

Table 5 - Statistical error data

Predicted Characteristic	Errors	Minimum	Average	Maximum	Standard Deviation
Tensile strength	Absolute Errors (MPa)	0.0028	0.1291	0.2582	0.0833
	Relative Errors	0.0892%	3.8737%	7.6926%	2.7693%
Compressive strength	Absolute Errors (MPa)	0.0423	0.5286	1.0270	0.3097
	Relative Errors	0.2700%	3.0696%	6.4120%	1.9100%

Figure 9 - Correlation between actual and predicted tensile strength values

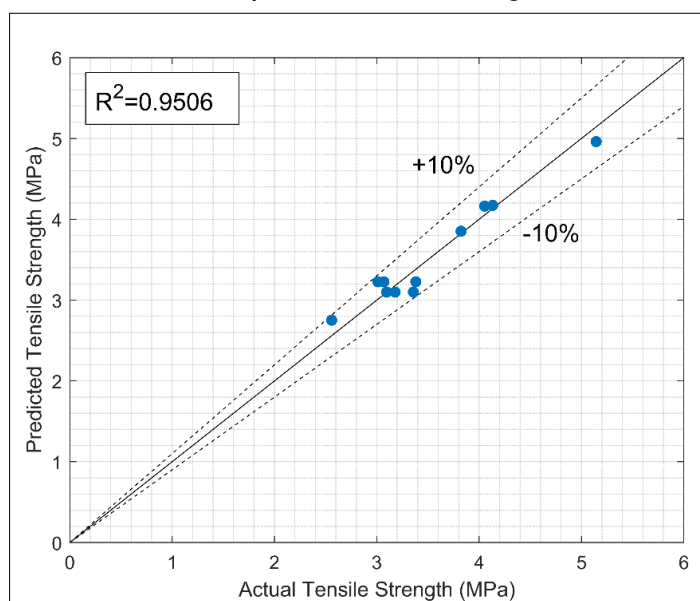
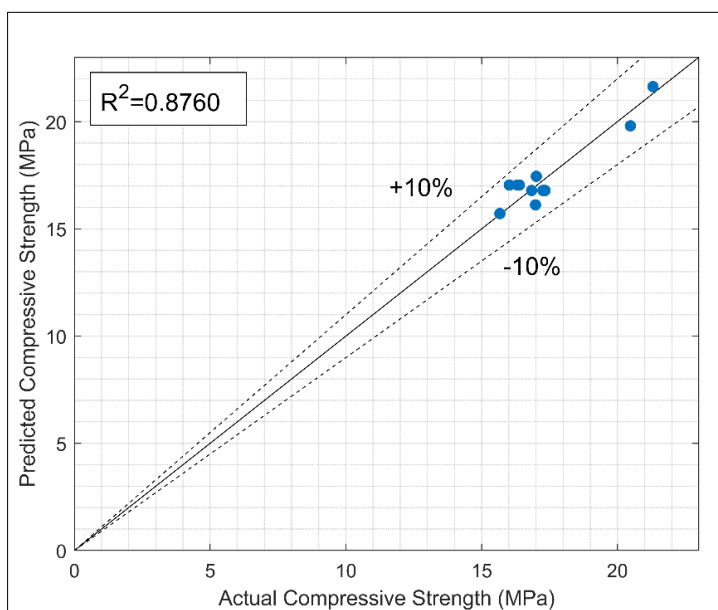


Figure 10 - Correlation between actual and predicted compressive strength values



Assuming that the ELM-T and ELM-C models have been implemented to assist in the dosing of mortars similar to those presented in this study, it is worth emphasize that the values predicted by them should be within the expected margins of error, as can be seen in Table 05. Furthermore, it is worth noting that, although the predicted values may fall within an acceptable range, the models predicted values both above and below the actual data, generating positive and negative errors, as can be seen in Figures 7 and 8. In other words, when using the models to predict the strengths of mortars reinforced with fibers from the babassu coconut epicarp, even if the absolute errors are at acceptable levels, it is possible that both models output values above or below what will actually be obtained during the material production. This occurs due to the models generating process, as the ELM algorithm trains the neural network aiming to obtain the smallest squared error, and in this context, only the magnitude of the errors is taken into account, disregarding their sign. The results obtained show that the models predicted actual data with a good approximation. Nevertheless, it was not possible to direct the models to predict data with any preference for error sign due to the type of training method.

In addition to the good predictability of the ELM-T and ELM-C models, it is worth mentioning that both were implemented using single-hidden layer neural networks, featuring only 6 and 7 hidden neurons, respectively. Despite the complexity in the relationship between the proportions of materials used in mortar production and the obtained strength values, the models were able to capture such relationship with a simple structure, enabling the application of both without significant computational efforts.

Although the ELM-T and ELM-C models have shown good performance in predicting tensile and compressive strengths, it is important to emphasize that these results reflect an initial study focused only on mortars reinforced with fibers from the babassu coconut epicarp and it is not possible to generalize the use of the models to predict strengths of mortars reinforced with other types of natural fibers.

Conclusion

To obtain a tool capable of predicting the tensile and compressive strengths of mortars reinforced with fibers from the babassu coconut epicarp, this study generates and uses an experimental database with 51 samples and proposes modeling using ANNs trained with ELM to estimate such characteristics.

Regarding the experimental procedure, it is expected that fiber-reinforced composites will exhibit better tensile strength results when compared to reference mixtures. However, in this research, this did not occur. It is estimated that the lack of fiber treatment contributed to the results. On the other hand, the energy absorption capacity without deformation of composites reinforced with fiber from babassu coconut epicarp is higher compared to reference mortars, even after matrix cracking. In other words, despite the reduction in strengths, the use of fiber from babassu coconut epicarp as reinforcement under the conditions presented in this study is advantageous in applications where greater toughness and higher impact resistance are targeted.

With regard to the proposed models, when defining the network topology, the number of neurons in the input and output layers remained fixed (6 and 1, respectively). For the hidden layer, the appropriate number of neurons was determined by comparing some heuristic rules through cross-validation. The Fletcher-Gloss rule was the most suitable for defining the number of hidden neurons. This rule indicates that the most promising number of hidden neurons for networks designed to predict tensile and compressive strengths are 6 and 7, respectively.

A model was generated to predict tensile strength (ELM-T) and another one to predict compressive strength (ELM-C). To assess the predictive capacity of the models generated, predicted values and actual data were compared using absolute errors and coefficient of determination (R^2). Both the ELM-T and ELM-C models showed an average absolute error of less than 1 MPa. Moreover, looking at the correlation between the actual and predicted strengths, all the points remain within a range of -10% and +10% of the identity line with a coefficient of determination equal to 0.951 for the ELM-T model and equal to 0.876 for the ELM-C model. This shows that both models performed well in predicting the characteristics for which they were created. It is possible to recommend them as a tool for dosing of mortars reinforced with fibers from the babassu coconut epicarp. However, it is worth noting that the proposed models are not intended for predicting tensile and compressive strengths of composites reinforced with other types of fibers.

It is also noteworthy that babassu is an abundant product in the region where this research was conducted, and any projects involving the utilization of babassu parts are likely to benefit several cooperatives that rely on it as their main source of income. Furthermore, this product can be a good alternative as a renewable material in the construction industry.

Furthermore, there is still much to be studied regarding this type of fiber to better understand and exploit its characteristics and facilitate its use in composites with cementitious matrices with improved mechanical

performance. For this purpose, more laboratory research needs to be conducted, which typically involves activities that tend to be laborious, time-consuming, and costly. However, the use of ELM-T and ELM-C models can assist in this process by predicting the tensile and compressive strengths of the mixtures intended for production, which constitutes an important contribution of this study.

Based on the research findings, the following topics for future studies are suggested:

- (a) applying treatment to the fibers to analyze their effects on composites with cementitious matrices, and comparing them with the effects of the fibers in their natural state;
- (b) verifying other characteristics of the composite developed, to learn more about its properties;
- (c) developing a model with multiple outputs to carry out the predictive process with a single topology;
- (d) generating new predictive models using other techniques, for comparison purposes with the models proposed in this study; and
- (e) determining ideal quantity of materials for the composite to achieve the desired characteristics using optimization algorithms applied to the implemented models.

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