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EVALUATING MECHANICAL PROPERTIES OF UNFIRED CLAY STRUCTURES USING ARTIFICIAL NEURAL NETWORKS (ANN) FOR HERITAGE CONSERVATION

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Abstract

Conservation of historical and vernacular architecture often involves the use of traditional materials such as unfired clay, which require precise mechanical characterization for effective preservation strategies. Experimental analysis for determining the compressive and flexural strengths of these materials can be time-consuming and costly. To address this, the present study aims to streamline the process by leveraging artificial neural networks (ANN). Two ANNs were developed and trained using experimental data from laboratory tests on unfired clay matrices. The trained models provided accurate predictions of mechanical properties, achieving an error rate of less than 1% for test values. These results demonstrate the potential of ANNs as efficient tools for predicting the mechanical behavior of unfired clay, offering significant time and resource savings in the conservation field. This approach enables more effective preservation and restoration of structures that utilize unfired clay, supporting efforts to maintain architectural heritage.

***Keywords**: Artificial neural network; Flexural strength; Compressive strength; unfired clay*

Introduction

Artificial neural networks (ANNs) can learn to describe and solve problems in a very short time without requiring a specific program. Creating a neural network is only possible if the input and output data are known. Based on parameters determined experimentally in the laboratory by non-destructive methods, ANNs have been developed that can predict the physical and mechanical characteristics of different materials, as well as computational relationships for materials or mixtures of materials with inhomogeneous behavior in structure.

M.V. Vasic et al. [1] investigated the effects of particle size distribution on the physico-mechanical characteristics of unfired clay bricks. The study included 139 clay samples and ANN models used 60% of the data for training, 20% for testing and 20% for validation. The input data included macro-oxide amounts, mineralogical content, 0.063 mm particle amounts and carbonate content and the output data was moisture, plasticity coefficient, direct sun shrinkage and compressive strength of the unhardened clay bricks

H. Limami et al. [2] developed another forecasting model using machine learning algorithms to predict the properties of brick samples with different percentages of additives. To improve the thermal, mechanical and physicochemical performance of clay bricks, waste plastics were used as additives.

A neural network requires sufficient training data to correctly predict the desired input-output relationship. *J.D. Sitton et al.* [3] *and J.D. Sitton & B.A. Story* [4] used input and output

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data obtained from laboratory and field tests on several soil samples. The values from the field tests were used as input data in the classification network and the results from the laboratory tests as output data. This approach allows fast and accurate classification of different soils based solely on qualitative and quantitative soil analysis by processing field test data instead of laboratory test results.

G.Q. Lan et al. [5] optimized the compressive strength of the unfired clay matrix using a neural network. This was trained to consider the influence of the specimen bonding arrangement, h/t ratio and the compressive strength of the matrix.

Artificial Intelligence (AI) can tackle complex problems requiring advanced knowledge of mechanics, mathematics, physics and attention to computation. Today, there are numerous AI applications, such as genetic algorithms, fuzzy systems, artificial neural networks and robotics, which are helping to advance scientific research in the field of construction.

Local raw materials represent a promising opportunity for sustainable development. Tapping the potential of these categories of materials requires innovative approaches for their further processing and use. Clay has been used for centuries in traditional construction, being used since ancient times in the form of unfired bricks, plaster or mortar.

Clay is a sedimentary rock, whose main ingredient is aluminum silicate (kaolinite) with colloidal appearance and binding properties. The main characteristic of clay is its ability to absorb large quantities of water, making it a soft, ductile mass that is easy to mold into any shape. The more loam the earth contains, the more moldable it is. The sandier (looser) the clay is, the more unsuitable it is for shaping [6].

The high degree of plasticity of clay-based mortar is one of the essential characteristics that promotes it for conservation work on built heritage. The workability of clay mortar as well as its ability to adapt to long-term structural changes facilitates the restoration of delicate details of historic buildings without compromising their authenticity [7-12].

This paper aims to study a method for the evaluation of the mechanical strengths of unfired clays using artificial neural networks.

Experimental part

Materials

There are several types of clay, among the most common are: raw clay, metakaolin, bentonite, nanoclay, organic clay and other calcined clays. The following minerals are described in the literature: quartz, kaolinite, kaolinite, illite, silica, silica, sepiolite, montmorillonite, muscovite and concresol.

Clay is a natural non-hydraulic binder; of all clays, the most commonly used in building materials are the chemically active montmorillonite clays, while kaolinitic clays, characterized by their low plasticity, are suitable for the ceramics industry.

Clays are composed of lamellar particles with a size smaller than 2μm (clay), sizes between 2-20μm (dust) and sizes larger than 20μm (sand). Figure 1 illustrates the ternary diagram for the five types of clay used in this study.

The proposed experimental models include a matrix composed of 70% fresh clay and 30% aggregates (commercial sand, with grain sizes between 0/1 and 0/4mm and river aggregates 4/8mm granular class), with a water/clay ratio that varies.

The clays used were collected from:

- (AG1) – Solești area, Vaslui county;
- (AG2) - Codăești area, județul Vaslui county;
- (AG3) - Cârlig area, Iași county;
- (AG4) – soaked (dump), Iași county;
- (AG5) – raw clay, Iași county;

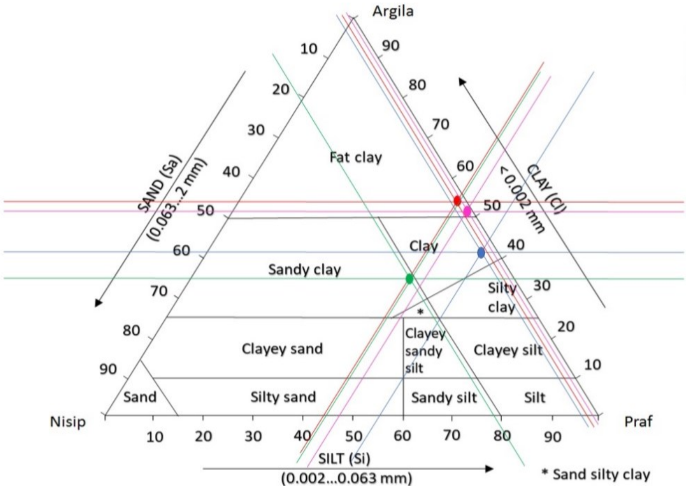


Fig. 1. Soil ternary diagram

Methods

The study was carried out on a batch of 120 prismatic specimens with dimensions of 40x40x160mm (Fig. 2). For each type of proposed mixture, 24 samples were tested according to SR EN 1015-3:2001/A2:2007 - *Methods of test for mortar for masonry - Part 3: Determination of consistency of fresh mortar (by flow table)*, to obtain the results on this parameter.

Fig. 2. 40 x 40 x 160mm experimental samples

Experiments Carried Out at Nird Urban-Incerc Incerc Laboratories, Iași Branch

The principle of this method was to place the conical mold on the circular table, where it was filled with the fresh mixture in two layers. Each layer was compacted with a metal may. After removal of the mold, 15 shocks were applied within a 15 second interval, followed by measurement of the average diameter of the sample.

The specimens were produced according to the following procedure:

i. determination of the moisture content of the constituents by heat-drying in a temperature-controlled oven at 105°C until constant mass was reached;

ii. introduction of clay and water into the vat, followed by mechanized mixing for three minutes; different ratios of water/clay (0.23÷0.60) were used to determine the optimum amount of water required to ensure satisfactory workability;

iii. addition of the aggregates and mixing for another 3 minutes until homogenized;
iv. immediate pouring of the clay composite into metal test specimen molds;
v. demolding of the samples after three days and maintaining them under laboratory conditions at 20±2°C and 65±5% relative humidity until testing.

The mechanical strengths were determined according to SR EN 1015-11:2020 - Test methods for masonry mortars (Part 11: Determination of flexural and compressive strength of hardened mortar). Strength values were experimentally determined for the five mixtures, 90 days after casting. The flexural strength wa determined by each individual prism, while the compressive strength was determined by the half-prism (Figs. 3 and 4).

Fig. 3. Flexural strength testing of clay composite (AG3, water/clay ratio 0,4, sample 3 of 6)

Fig. 4. Compressive strength testing of clay composite (AG3, water/clay ratio 0,4, sample 3 of 6)

The average compressive strength determined on the structures of the unfired clay matrices ranged between 3.64MPa for AG4 and 6.87MPa for AG3 for the coefficients of variation ranging between 2.59÷14.51%. Thus, following the analysis of the results obtained, the AG2 mixture showed superior results, both in the case of flexural strength (1.38MPa), with a coefficient of variation of 6.90 (Fig. 5) and in the case of compressive strength (4.45MPa) and coefficient of variation of 5.38 (Fig. 6).

Compressive strength depends on the granular distribution of the soil, water content, mineral type and static or dynamic compaction. If the sand particles have been distributed to give a minimum compact volume and the spaces between the sand grains are completely filled with clay, then the maximum density is reached, hence the compressive strength.

A low compressive strength may occur if the loose clay matrices have been exposed to wind and sun or if large quantities of sand are introduced. Low strength but also a high expansion/contraction ratio can cause severe structural damage.

In conclusion, the clay used for the production of AG2 mixture remains satisfactory in terms of mechanical strength results.

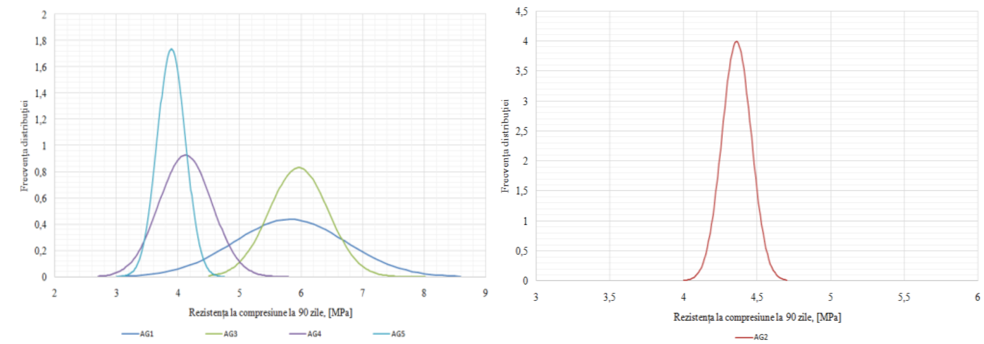


Fig. 5. The distribution of compressive strength results for the five types of unfired clay samples

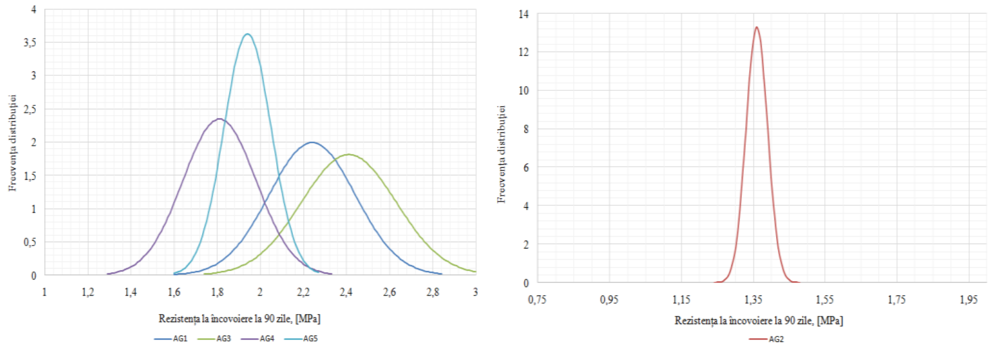


Fig. 6. The distribution of flexural strength results for the five types of unfired clay samples

Artificial Neural Networks

In this paper, two neural networks were proposed in order to determine the compressive and flexural strength of unfired clay matrices. The values recorded from the tests were used to train the two networks.

The operating principle of the artificial neuron [7], with six inputs and a single output, can be represented as a block diagram (Fig. 7).

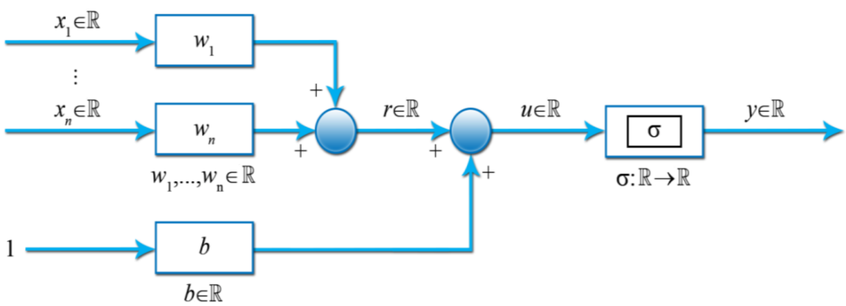


Fig. 7. Block diagram of an artificial neuron with n = 6 inputs

To the input signals, x_i, where i = 1…6 weighted with scalar values, w_i, where i =1…6 was added an input signal with a specified value, 1 and weight b. The adjustment of the values of the parameters w and b was aimed at improving the learning capacity of the artificial neuron. The sum of all the weighted signals, denoted by u, where u ϵ IR, was used in the activation function (σ), expressed algebraically with Eq. 1:

$$u = w_1 \cdot x_1 + \cdots + w_6 \cdot x_6 + b = \sum_{i=1}^{6} w_i \cdot x_i + b \quad (1)$$

where: $\boldsymbol{x}$ is the column vector containing the entries,

$$\boldsymbol{x} = [x_1 \ldots x_6]^T \in R^6; \quad (2)$$

$\boldsymbol{w}$ is the line vector containing the weights,

$$\boldsymbol{w} = [w_1 \ldots w_6] \in R^{1x6} \quad (3)$$

The neural network trained to determine mechanical strengths is a two-layer feedforward network for which the output of one layer is the input to the next higher layer. There is a hidden layer between the input and output layers [8] Two-layer feedforward networks are suitable for problems that cannot be modeled with linearly separable functions (Fig. 8).

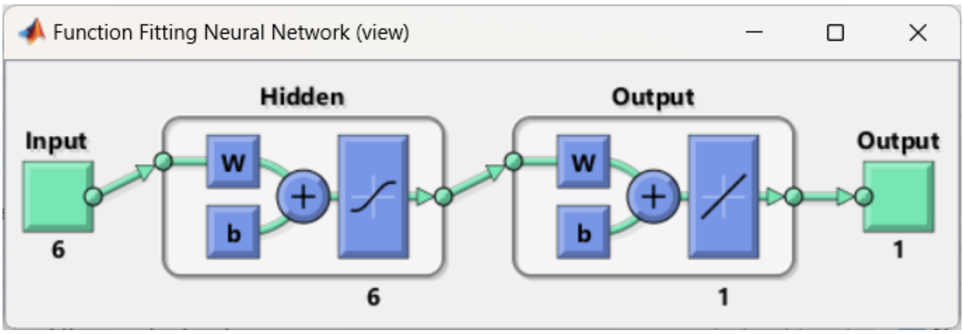


Fig. 8. The architecture of the artificial neural network trained to predict the compressive strength of an unfired clay matrix

The number of neurons per layer were determined based on several trial runs. The training algorithm of ANN is backpropagation and aims to minimize the mean squared error by the Levenberg-Marquardt method. This method is very common in practice for problems containing small training vectors. The network is dependent on activation function, learning rate, weights and bias parameters. The signal propagates forward and the error propagates backwards.

The ANN inputs are:

- the density of the unsaturated clay matrix, D (kg/m^3);
- water to clay ratio (dimensionless), a/A;
- sample mass, m (grams);
- clay, dust, sand content in clay soil, p% (percent).

One network predicts as output the compressive strength of the matrix (MPa) and the second network, using the same network input data, determining the flexural strength of the matrix. A total of 84 data (70%) were used for training, 18 data (15%) for validation and 18 data (15%) for testing, a total of 120 data needed to train the neural network (Table 1).

The input data were entered as a matrix of 120 rows (number of samples) and six columns (number of parameters) and the output data as a matrix of 120 rows (number of samples) and one column (one parameter). The test data has no effect on the network training.

Table 1. Numerical values used in ANN to determine mechanical strength

Sample	Density (kg/m^3)	Mass (kg)	Water / clay ratio	Characteristics of mixtures fresh claye mixtures resulting from the particle size curve (%) Clay	Dust	Sand	Flexural strength (MPa)	Compressive strength (MPa)
Artificial neural network training data								
1	2053.998	363.90	0.450	34.260	45.12	20.62	2.4130	3.1625
2	2040.191	360.90	0.450	34.260	45.12	20.62	2.3524	1.9812
...	...	...	...	...	...	...	...	...
84	1969.319	382.09	0.470	51.000	48.18	0.82	2.1168	3.8000
Artificial neural network validation data								
1	1971.946	394.33	0.450	51.000	48.18	0.82	2.0069	4.1375
2	2107.987	373.26	0.450	34.260	45.12	20.62	2.4561	4.69375
...	...	...	...	...	...	...	...	...
18	2106.637	453.88	0.350	41.410	54.64	3.95	1.6835	7.2625
Artificial neural network test data								
1	1990.995	392.35	0.450	51.000	48.18	0.82	2.1773	5.01875
2	2088.976	367.67	0.500	34.260	45.12	20.62	2.2325	4.2875
...	...	...	...	...	...	...	...	...
18	1998.925	485.76	0.250	52.710	43.77	3.52	1.4245	4.35625

Results and discussion

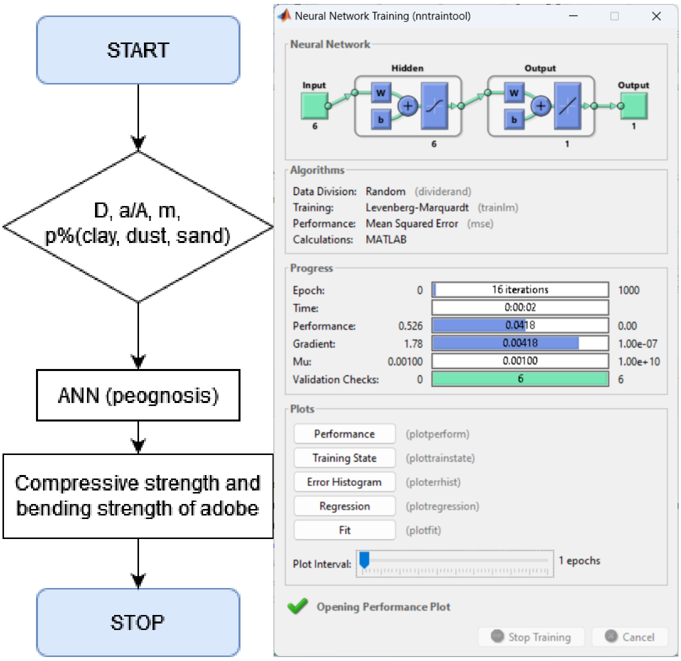
The principle of using the neural network is described in the logic scheme shown in Figure 9. The time interval required for the neural network to predict the compressive strength for a single array is 2-3 seconds.

The accuracy of the results predicted with ANN can be followed by the graphs generated by the network at the end of the training (Fig. 10).

Following the training of the artificial neural network, a function has been created, which can be called in Matlab program and which predicts the flexural strength of unfired clay samples. In the following lines of code in Matlab it is explained what this function entails:

```
Function [Y,Xf,Af] = myNeuralNetworkFunction (X,~,~)
% myNeuralNetworkFunction - neural network simulation function.
% Generated by NeuralNetworkToolbox function genFunction, 12-Sep-2024 20:49:03.
% [Y] = myNeuralNetworkFunction (X,~,~) takes these arguments:
%   X = 1xTS cell, 1 inputs over TS timsteps
%   Each X{1,ts} = 6xQ matrix, input #1 at timestep ts.
% and returns:
%   Y = 1xTS cell of 1 outputs over TS timesteps
%   Each Y{1,ts} = 1xQ matrix, output #1 at timestep ts.
% where Q is number of samples (or series) and TS is the number of timesteps.
```

myNeuralNetworkFunction([1998.925;485.76;0.250;52.710;43.77;3.52])
ans =1.4247
myNeuralNetworkFunction1([1998.925;485.76;0.250;52.710;43.77;3.52])
ans = 4.316



a. ANN logic scheme **b**. ANN training

Fig. 9 Artificial neural network principle

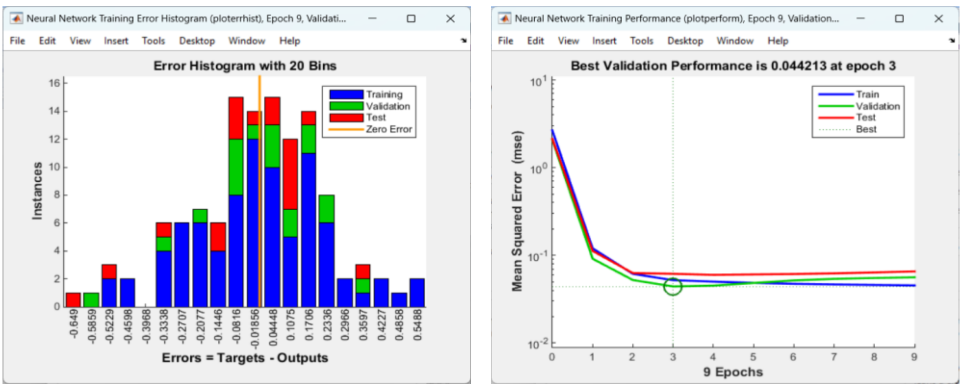


Fig. 10. Corectitudinea rezultatelor prognozate cu ajutorul ANN

By analyzing the results predicted by the function „myNeuralNetworkFunction" and those determined experimentally, an error of less than 1% between the values is observed. Similarly, the function „myNeuralNetworkFunction1" was created, which when called in Matlab program can predict the compressive strength of unweathered clay samples (Table 2).

Table 2. Error recorded between the two methods to determine the mechanical strengths for the unfired clay matrix

Experimental compressive strength (MPa)	*ANN compressive strength (MPa)*	*Error*	*Experimental flexural strength (MPa)*	*ANN flexural strength (MPa)*	*Error (%)*
4.3562	4.316	0.936	1.4245	1.4247	0.014
4.4938	4.487	0.152	2.1699	2.1601	0.451

Conclusions

The use of Artificial Neural Networks (ANN) to determine the mechanical strength of unfired clay matrices is an efficient and innovative solution with numerous advantages for researchers and practitioners. In the context of traditional testing procedures, the introduction of ANN significantly simplifies and speeds up the evaluation process, providing a modern method with multiple benefits:

a) Simplification of the experimental process - experimental tests can be replaced or supplemented by ANN modeling. Neural networks simulate the complex relationships between physical matrix parameters (water-clay ratio, mass, density and soil composition) and mechanical behavior (compressive and flexural strength);

b) Reduced testing time - the high processing speed of ANN allows validation and testing of the neural network with experimental data;

c) Accuracy and reliability of predictions - properly trained artificial neural networks are able to predict with a high degree of accuracy the mechanical behavior of unfired clay materials. These predictions are based on an initial, tested and validated dataset. Once calibrated, ANN can provide accurate results, comparable to those obtained by classical experimental methods, but in a much shorter time and with reduced effort.

d) Optimizing the use of resources - traditional testing methods involve the use of significant amounts of materials and specialized equipment for each physical sample. The use of artificial neural networks allows optimization of resources as reducing the number of physical tests decreases material consumption and reduces associated costs.

e). Possibility to quickly adjust parameters - by changing input parameters (such as water-clay ratios or matrix density), the network can quickly generate new predictions for the mechanical strength of the material. This rapid simulation capability allows the composition of clay mixtures to be optimized according to the specific requirements of each project.

This study demonstrates the potential of artificial neural networks (ANN) as a reliable and efficient alternative to traditional experimental methods for determining the mechanical properties of unfired clay matrices. By training two ANNs with data from laboratory tests, compressive and flexural strengths were accurately predicted with an error rate of less than 1%. This level of precision not only validates the applicability of ANNs in this context but also underscores their value in reducing time and costs associated with material testing. The integration of ANN models in the study of traditional materials offers a promising pathway for conservation professionals, facilitating the assessment and preservation of heritage structures that utilize unfired clay. By enhancing our ability to predict mechanical behaviors swiftly and accurately, this approach supports more informed decision-making in conservation efforts, contributing to the sustainable preservation of architectural heritage [9-14]. Future work could expand upon this research by exploring other traditional materials and refining the neural network models for even broader applications in the field of conservation science.

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