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APPLICATION OF ARTIFICIAL NEURAL NETWORK IN PREDICTING COMPRESSION STRENGTH OF CLAY BRICK MASONRY PRISM

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ABSTRACT

Masonry is the oldest and most widely used building material in historical and modern structures. However, predicting the axial compressive strength of masonry works is still a challenge for the scientific community considering its diversity and complexity, which does not depend only on the mechanical properties of materials, but also depends on the geometrical characteristics for each component. This paper aims to predict the compression capacity of clay brick masonry prisms by using a machine learning technique. Artificial neural networks (ANNs) have attracted a lot of attention in recent years in many scientific fields for their capability to develop prediction models by training data. The ability of artificial neural networks (ANN) to predict the compressive strength of clay brick masonry prisms against experimental tests available in published journals will be examined. The proposed ANN model considered the essential parameters that would affect masonry strength, including the strength and the type of clay brick unit, mortar type, and slenderness ratio. After the ANN model was trained with the available 326 datasets, the proposed ANN model demonstrated a good ability to predict the compressive strength of clay brick masonry prisms. The model achieves a high value of the coefficient of determination around 0.91 which is better than the empirical models reported in published literature.

KEYWORDS: *brickwork, machine learning, prediction, strength*

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INTRODUCTION

Specifying the compressive capacity of clay brick masonry assembly is an essential step to designing a masonry structure. Designers can quantify the strength of masonry prism in compression by two methods. First, by assuming the strength based on models recommended by international design codes or by testing prisms, which more representing the actual construction and usually gives a higher accurate value. However, conducting compression tests to determine the actual compressive capacity of masonry prisms is not the usual practice considering material and labor costs and the required time for these tests to be conducted in the laboratory. Furthermore, the designers are left to rely on prediction models. The majority of these models available in the literature [1-11], including those used in design codes [12-14], are empirical expressions derived by experimental tests. Despite the earliest function of predicting compressive strength for masonry could be back to 1907 by Engesser [1], the behavior of masonry under comparison remains a continuous challenge for the scientific community considering its diversity and complexity. Also, that is related to the inhomogeneous and anisotropic nature of masonry components. Clay brick masonry is a typical brittle material built by bond clay bricks and mortar. These two components are mainly categorized by establishing each component's compressive strength. The ingredients and processes used in constructing each masonry component play an important role in gaining compressive strength. Clay brick units and mortar binder and their interfaces are equally playing an important role in heterogeneous masonry assembly. The global behavior of masonry structures is highly affected by the nonlinear behavior exhibited from the main parameters. That makes developing an analytical model to establish the axial compression capacity for masonry prism is complex and requires many parameters to describe the failure. Several analytical models [15-18] can be found in the literature.

On the other side, the empirical formulas proposed in the literature mainly calibrated by experimental tests conducted on masonry prisms to evaluate the compressive strength. That includes the formulas suggested by international design codes and guidelines. The slenderness ratio of masonry prisms and the compressive strengths of blocks and mortars are the most parameters considered in empirical expressions. However, the tests adopted to calibrate the empirical expressions are limited, and with new compressive tests coming out, the reliability and accuracy of the empirical expressions need to be reviewed.

In recent years, the artificial neural networks (ANNs) technique has received more attention for its ability to model the nonlinear behavior of the parameters and overcome the limitations of traditional calibration methods to provide reliable predictions. However, with artificial neural network technique advantages, no many scientific studies were conducted to describe the axial compressive behavior of masonry using ANN techniques. Zhang et al. [19] proposed an ANN model to predict the cracking patterns of masonry wallets vertically tested. Garzón-Roca et al. [20, 21] calculated the axial behavior of masonry walls and the compressive capacity of brick prims using the ANN model. Moreover, Plevris et al. [22] modeled the masonry failure under biaxial compressive stress by ANN techniques. To the authors' best knowledge, applying ANN techniques to simulate the axial compression behavior of clay brick masonry is limited. On the other hand, ANNs were used to solve various structural problems, including works conducted to predict the concrete mechanical properties using ANNs [23-29].

This work aims to structure an ANN model trained by an extended database to estimate the compressive capacity of un-grouted clay brick masonry prisms. The reliability and predictability of the proposed ANN model will be measured by comparing its performance with several empirical formulas available in the literature.

ARTIFICIAL NEURAL NETWORK MODEL

ANN model is a computational algorithm inspired by the biological nervous system. Typical ANN includes interconnected neurons arranged over at least three layers. ANN model processes input data in an input layer with one or more hidden layers and one output layer. All neurons are connected through the layers, and conversion is achieved by nonlinear mapping.

The backpropagation algorithm is used to train the multi-layered feedforward networks. The algorithm reduces the values of errors between the known targets and the inputs by continuously adjusting the values of weights and biases [30, 31]. In the forward stage, the sum of the input data multiplied by weights added to the bias is then processed in the activation function. The result will be passed to the next neuron in the next layer. In the backward stage, the error between the prediction and the known targets is minimized by updating the weights and biases. Values are propagated backward from the output layer to the input layer until the error would be in an acceptable range. In the present study, logistic activation functions were adopted in both hidden and output layers. A typical artificial neural network structure in this paper is illustrated in Figure 1.

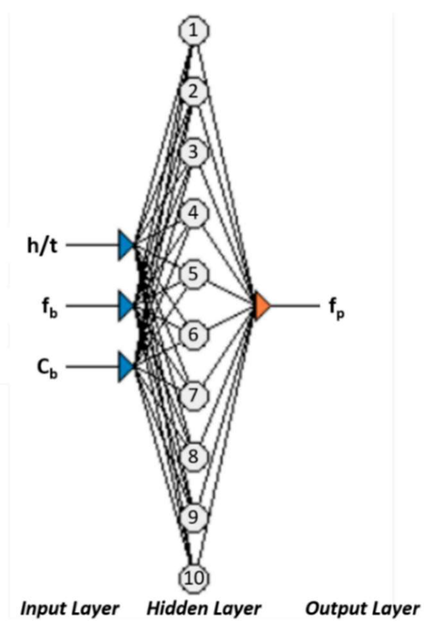

Figure 1 Typical artificial neural network structure.

Data collection

For successful training prosses of the ANN model, collecting a large database of experimental tests that comprehends the majority of factors that affect the compressive strength prediction for clay brick masonry prisms is necessary. Collecting data in the case of masonry is difficult for several reasons. First, it is necessary to limit the data to a certain type of masonry, considering the masonry build with a variety of materials combined with mortar of varying strengths. Some of the common materials used are brick, stones, and concrete. Second, not all the parameters were reported in the literature. In view of this, a large database composed of 904 data tests reported by Aryana [32] was considered. The data was reported in 23 different experimental studies [6, 33-52].

During the process of filtering the experimental data from Aryana dataset [32], it was only taken under consideration the prisms cured by the moist method for 28 days and constructed by full bedding without grout. Clay brick units compressive strength (f_b), mortar type (M, S, or N) according to ASTM C 270-19 [53], the ratio of masonry prism height to the thickness (h/t), brick unis type of hollow or solid was collected beside the masonry prisms compressive strength (f_p). The limit values of variables in the filtered dataset are listed in Table 1. The brick unit is only considered solid if the net area is more than 75% of its gross area and considered hollow units if it is less. The filtered dataset contains 326 tests divided between 124 hollow clay brick units and 202 solid clay brick units.

Table 1 The limit values of variables in the training dataset.

Variables	Min	Max	Average	Standard deviation	COV (%)
f_b (MPa)	34.00	105.98	68.24	22.37	33
f_m(MPa)	3.23	20.00	14.82	5.11	34
h/t	1.96	5.88	2.95	1.38	47
f_p (MPa)	13.55	54.98	29.76	9.09	31
C	0.75	2.42	1.79	0.62	34

The architecture of artificial neural networks

Literature has shown several parameters would affect the compressive strength of the clay brick prism (f_p). The compressive strength of brick unit (f_b), the slenderness ratio of masonry prism (h/t), unit type of solid or hollow, and the type as M, S, or N are the most critical parameters.

For taking into account the unit type and mortar type as numerical values, three coefficients were introduced. As mortar is usually classified by types based on the applications and strength ranges rather than specified strength as North American codes suggesting. The coefficients (C_b) and (C_m) were proposed to account for the brick unit type and the mortar type, respectively. $C_b = 1$ for solid brick unit and 0.5 for hollow brick. Furthermore, The coefficient $C_m = 1$ for N type mortar and 2.34 and 3.23 for Type S or M mortar. The coefficients (C), which is the result of the interaction between brick unit type and the mortar type, can be calculated as

$$C = C_b \times C_m \tag{1}$$

The artificial neural network model can be structured with different architectures depending on the complexity of the problem being simulated. In this case, the input layer consists of three neurons for f_b, h/t and C input parameters. The target layer is one neuron for the compressive strength of the clay masonry prism (f_p). The selection of the number of neurons in the hidden layer is arbitrary. Therefore, the number can be found by series of trails. A total of 15 different ANNs with various architectures were built and trained. All ANNs have one hidden layer with a number of neurons ranged from 1 to 15.

Normalizing the network inputs and output can improve the ANN training process and made it more effective. Inputs were normalized to a value fall between -1 and +1, where the upper and lower bounds for normalized output are 0 and 1. When the training process of the ANN model is finished, the model output is reversed back to the original target output value.

The dataset, which consists of 326 tests, is split into three subsets: training, validation, and test subsets, as given in Table 2. The distribution of tests across the subsets was random.

Table 2 Data partition of the training dataset.

Subsets	Data	Percentage (%)
Training set	222	68
Validation set	52	16
Test set	52	16
Total	326	100

The training subset is mainly used to train the ANN model and calculate weights and biases to minimize network error. The error is measured in the validation subset during training if it keeps increasing, the training is stopped, and best network weights and biases are returned. The test subset is not used at all during the training process. However, it is used to monitor the ANN model's ability to generalize the predictions for unseen data.

RESULTS AND DISCUSSION

Each of 15 ANNs was trained on the dataset, and the statistical performance was obtained. Three statistical indicators were calculated to compare the models' performance. the indicators are average the ratio of $f_{p(exp)}/f_{p(theo)}$, determination coefficients (R^2) and coefficient of variation (C.O.V.) between experiments tests and predicted values. The selection of the best ANN model was based on the highest determination coefficients. Based on training results, the best performance of the ANN model is 3-10-1, which corresponds to ANN architecture with three input neurons of f_b, h/t, and C, ten neurons in the one hidden layer, and an output layer with one neuron of f_p. The performance of the proposed ANN model is compared with seven empirical formulas reported in the scientific literature [1, 3, 6-8, 11, 21].

Several mathematical expressions have been suggested to predict the masonry compressive strength in literature. The earliest expression could be back to 1907 by Engesser [1]. Mann [3] suggested a model calibrated by experimental tests of masonry prisms made with brick, concrete, and sandstone with a five slenderness ratio. Dymiotis and Gutlederer [7] proposed a polynomial equation considering the effect of brick and mortar strengths on the axial capacity of the prism. Kaushik et al. [8] suggested a model based on masonry prisms tests with different bricks and mortar types. Bennett et al. [6] conducted tests on clay tile prisms and proposed a simple expression for predicting the prism axial compression capacity by knowing the masonry unit strength. Garzón-Roca et al. [21] apply a multiple linear regression analysis on 96 datasets of clay bricks prisms to propose a new model. Kumavat [11] proposed an analytical model for clay brick masonry. Several mathematical expressions with the parameters adopted by each expression are reported in Table 3. The principal parameters adopted in the expressions for predicting the prism axial compression capacity are the compressive strength of the masonry units (f_b), and the compressive strength of mortar (f_m).

Table 3 Masonry compressive strength models reported in published literature.

No.	Reference	Year	Model
1	Engesser [1]	1907	$f_p = \frac{1}{3} f_b + \frac{2}{3} f_m$
2	Mann [3]	1982	$f_p = 0.83 f_b^{0.66} f_m^{0.18}$
3	Dymiotis & Gutlederer [7]	2002	$f_p = 0.3266 f_b \times \left(1 - 0.0027 f_b + 0.0147 f_m\right)$
4	Kaushik et al. [8]	2006	$f_p = 0.317 f_b^{0.866} f_m^{0.134}$
5	Bennet et al. [6]	2007	$f_p = 0.3 f_b$
6	Garzon Roca et al. [21]	2013	$f_p = 0.53 f_b + 0.93 f_m - 10.32$
7	Kumavat et al. [11]	2016	$f_p = 0.69 f_b^{0.6} f_m^{0.35}$

The average, determination coefficients, coefficient of variance of the ratio between the entire experimental dataset, and theoretical prediction of compressive strength of clay brick prims are reported in Table 4. The comparison between prediction models and experimental tests was visualized in Figure 2 and Figure 3. The spread of the prediction values indicates low performance and week ability to predict the behavior of clay brick masonry prisms in compression. The average ratio of the experimental to predicted strength is found to be 0.998 for the ANN proposed model with a low coefficient of variation around 10%. The proposed ANN model showed the best performance regarding the three statistical indicators. The ANN model has the best matching with the tests compared to the seven empirical models.

The predictions models proposed by Engesser [1], Mann [3], and Kumavat et al. [11] showed a very low coefficient of determination R^2 values. In the case of Engesser [1] and Garzon Roca et al. [21], the average ratio between experimental results and predictions shows unconservative estimation for compressive strengths of clay brick prisms.

Table 4 The comparison between prediction models and experimental tests.

No.	Models	R^2	$C.O.V$	$\left(\frac{f_{p(exp)}}{f_{p(theo)}}\right)_{average}$
1	ANN	0.909	0.102	0.998
2	Engesser [1]	0.170	0.286	0.924
3	Mann [3]	0.147	0.294	1.432
4	Dymiotis & Gutlederer [7]	0.262	0.264	1.363
5	Kaushik et al. [8]	0.293	0.260	1.780
6	Bennet et. al. [6]	0.524	0.241	1.515
7	Garzon Roca et al. [21]	0.212	0.291	0.775
8	Kumavat et al. [11]	0.000	0.431	1.473

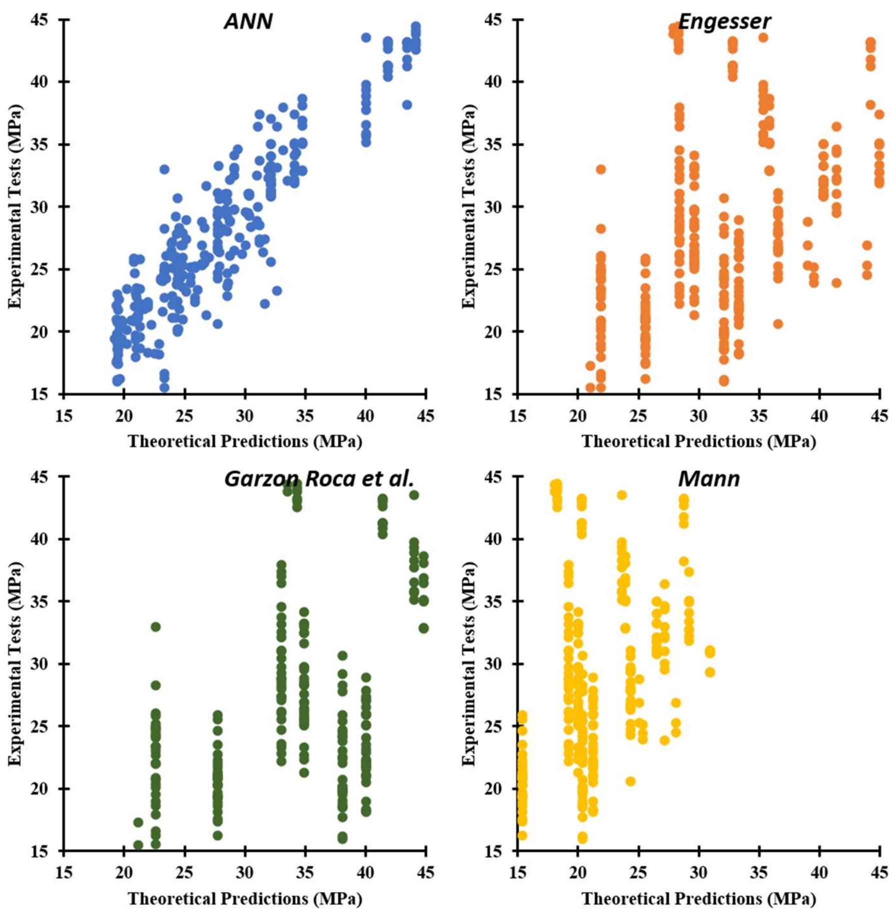

Figure 2 The comparison between prediction models and experimental data.

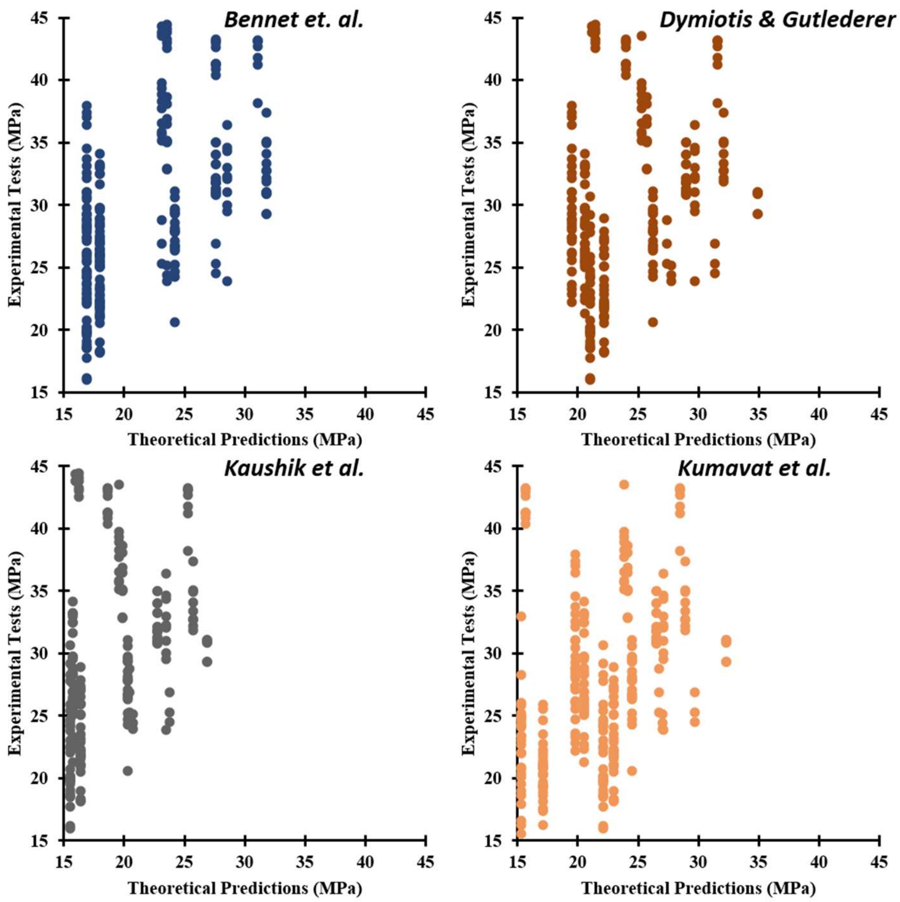

Figure 3 The comparison between prediction models and experimental data.

CONCLUSIONS

In this paper, the machine learning technique of the ANN model was structured to estimate the axial compressive strength of un-grouted full bedded clay brick masonry prisms. An extended database of 326 experimental tests collected from published literature was used to train, validate, and test the ANN model. The following conclusions were drawn:

- The proposed ANN model, which contains ten neurons in a single hidden layer trained by the batch backpropagation algorithm, showed good performance in predicting the compressive strength of clay brick masonry prisms.
- In general, the proposed ANN model has better performance for predicting the compressive strength of clay brick masonry prisms compared to empirical expression published in the literature.

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