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A Machine Learning Approach for Predicting the Compressive Strength of Masonry Walls: An Artificial Neural Network Model

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Abstract

Masonry walls have long been a critical element in construction due to their durability, fire resistance and aesthetic value. With the increasing integration of advanced technologies like artificial intelligence (AI) and machine learning (ML) in the construction industry, this study aims to propose a simple yet reliable model for evaluating the compressive strength of masonry walls using ML techniques. A larger data set was constructed for numerical analysis, expanding on previous data availability. The results indicate that the artificial neural network model achieved very satisfactory values of the accuracy parameters, demonstrating the reliability of the model. These findings suggest that ANN, can provide accurate predictions for the compressive strength of masonry walls, offering a promising tool for improving design and construction practices. The adoption of such models can significantly enhance the efficiency, safety, and cost-effectiveness of masonry wall assessments in the future.

Keywords: masonry walls, artificial neural network, compressive strength, mortar, masonry unit, machine learning.

1 Introduction

Masonry walls have been a fundamental component of construction for centuries, known for their durability, fire resistance, and aesthetic appeal. These walls are constructed using individual masonry units such as bricks, concrete blocks, stones, and are bonded together with mortar or glue. The versatility of masonry allows it to be used in various types of structures, from residential buildings to large commercial complexes. Traditionally, masonry walls have been valued for their strength and ability to provide thermal and acoustic insulation, making them a preferred choice in many architectural designs [1].

In recent years, the construction industry has witnessed a significant shift towards the integration of advanced technologies, particularly artificial intelligence (AI) and machine learning (ML) [2]. The adoption of AI and ML in construction is not only improving the quality and safety of masonry walls but also reducing costs and project timelines. As the construction industry continues to evolve, the role of AI and ML in the construction of masonry walls is expected to grow, paving the way for more innovative and efficient building practices [3].

1.1 Literature survey

In previous research various ML techniques were applied to estimate the strength of masonry walls that are subjected to compressive loading. Due to the fact that preparing samples for experimental tests is costly and requires special equipment, the number of studies is limited and mostly based on dataset gather from other scientific papers.

For example, Sathiparan [4] relied on 18 scientific papers, thanks to which was able to build a dataset containing 512 data points. The study compares the accuracy of such models as: linear regression (LR), artificial neural networks (ANN), K-nearest neighbours (KNN), random forest regression (RF), extreme gradient boosting (XGB), support vector regression (SVR). The models were built based on information about the strength of the masonry and mortar as well as the ratios of height-to-thickness of the investigated wall and the percent of the masonry unit in the whole element. It has been proved that among the models the neural network was the most accurate with very high values of the coefficient of the determination R^2 above 0.94 for training and testing processes. Moreover, as the most important input parameters for predicting the compressive strength of the wall were as follows, compressive strength of the grout, compressive strength of brick, ratio of bricks area to whole wall cross section area, height to width, compressive strength of mortar and length to width ratio of the wall.

In case of work performed by Len et al. [5], the comparison was done between the ANN and adaptive network-based fuzzy inference system (ANFIS). For this evaluation the 72 data was used in dataset where 66 was collected from other experimental studies and 6 samples were prepared by the researcher. It has been proved that both of the models were accurately predicting the compressive strength of wall made of earth block masonry. The ANFIS model slightly outperformed the ANN with very high value of the coefficient of linear regression R equal to 0.983.

With 102 gathered samples from the literature survey, Fakharian et al. [6], proposed a comparison of various models: ANN, combinatorial group method of data handling (Combinatorial GMDH), genetic expression programming (GEP). In this case the ANN outperformed the other models with the only algorithm able to obtain the accuracy, evaluated based on coefficient of determination R^2 above 0.9.

Sharafati et al. [7], focused more on comparison between SVR, decision tree (DT), and bagging regression (BGR). For training and testing process of the models, the dataset containing 90 samples were built also from the literature survey. The Authors during training and testing process check also the various division of the subsets for those processes, as follows: 80% of dataset for training and 20% for testing, 75% and 25% and 70% and 30%. For, all of the afore-mentioned models the most accurate were the models with the first division scenario (80-20), and the most accurate algorithm was BGR with R^2=0.97, whereas the least accurate was SVR.

In research done by Asteris et al. [8], the comparison of the accuracy of prediction the masonry walls compressive strength was done using ANN, and genetic programming (GP). The sensitivity analysis results indicate a strong correlation between masonry compressive strength and masonry unit compressive strength, identifying it as the most influential factor. Additionally, mortar thickness significantly affects masonry wall compressive strength, followed by the masonry prism height-to-mortar thickness ratio, masonry unit height, and the mortar thickness-to-masonry unit height ratio. Among these, mortar compressive strength has the least impact on masonry wall strength. Furthermore, the developed soft computing models outperform existing literature-based expressions, mostly standards. Notably, the ANN model achieves an R-value of 0.948 for the entire dataset, compared to the highest literature-based value of 0.806.

In work done by Gholami et al. [9], more advanced algorithms were used such as: optimized convolutional neural network (OCNN) using Cuckoo search optimization algorithm (CS), extreme learning machine (ELM), DT, Committee machine (CM). The Authors have gathered the open-sourced data of 96 experimentally tested samples with the division of 67 samples set for training and 19 for testing. All of these algorithms outperformed other afore-mentioned algorithms with very high accuracy evaluated using coefficient of determination R^2 above 0.98.

Another application of advanced machine learning techniques to estimate the compressive strength of structural masonry walls was done by Marulasiddappa et al. [10]. Three algorithms—Gradient Boosting Trees (GTB), Elman Neural Networks (ENN), and Multivariate Adaptive Regression Splines (MARS)—are utilized, with input data sourced from various literature sources, including Young's modulus of brick units (Eu), compressive strength of brick units (Fcu), Young's modulus of mortar (Em), and compressive strength of mortar (Fcm). To evaluate the effectiveness of each model, different statistical indices measuring both error and efficiency are computed. The analysis of these indices aims to determine the most suitable method for this application. Among the tested models, MARS demonstrates the highest accuracy and robustness across different input/output combinations, consistently outperforming GTB and ENN in the testing phase. The superior WI values obtained by MARS indicate its enhanced ability to generalize and fit unseen data more effectively than the other models.

1.2 Aim of the Study

The aim of this study is to construct a larger dataset for numerical analysis than has been previously available and to propose a simple yet reliable model for evaluating the compressive strength of masonry walls using machine learning techniques.

2 Collected data

As it was previously mentioned in the introduction, preparing the reasonable data set for building a machine learning model, requires lots of time consuming and costly tests, the authors decided to gather the data from the previous experimental studies. The data was collected from scientific papers as presented in Table 1. This dataset consists of 226 sets of values describing the properties of masonry units and mortars as possible inputs and the output that is compressive strength of wall. Analysing those studies the Authors decided to use as inputs used in training and testing processes of machine learning algorithms, the following parameters:

- **Compressive Strength of Mortar (MPa)**: This numerical variable represents the strength of the mortar assessed during the destructive compression test. Its representation measured in MPa is a result of the division of the measured during the test destructive force and the area of the standarised sample.
- **Compressive Strength of Masonry Unit (MPa)**: This numerical variable represents the strength of the masonry unit assessed during the destructive compression test. Its representation measured in MPa is a result of the division of the measured during the test destructive force and the area of the standarised sample.
- **Height to Width Ratio (dimensionless)**: The ratio of the heigth of the tested sample divided by its width.

Given that these are preliminary deliberations on the potential application of machine learning for the analysis of the compressive strength of masonry walls, an attempt was made to construct a model utilizing artificial neural networks with a single

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Cheema, T. S., & Klingner, R. E. Compressive strength of concrete masonry prisms. *ACI Journal Proceedings* [37]	1986
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National Concrete Masonry Association. Recalibration of the unit strength method for verifying compliance with the specified compressive strength of concrete masonry. *Report No. MR37, NCMA* [39]	2012
Andolfato, R. P., Camacho, J. S., & Ramalho, M. A. Brazilian results on structural masonry concrete blocks. *ACI Materials Journal* [40]	2007
Ramamurthy, K., Sathish, V., & Ambalavanan, R. Compressive strength prediction of hollow concrete block masonry prisms. *ACI Structural Journal* [41]	2007

Table 1: Summary of references where the data come from.

Parameter	Min	Max	Mean	Std.
Compressive Strength of Mortar [MPa]	0.47	40.50	12.01	9.79
Compressive Strength of Masonry Unit [MPa]	0.47	35.50	11.99	9.05
Height to Width Ratio [-]	0.90	5.75	2.98	1.14
Compressive Strength of Masonry Wall [MPa]	0.33	31.00	8.26	8.65

Table 2: Summary statistics of the collected data.

hidden layer. Such networks are widely employed in addressing engineering problems of this nature. The model training and testing process involved partitioning the dataset into three subsets: a training set comprising 70% of the data, a testing set representing 15%, and a validation set, which also accounted for 15%. The training process utilized the Levenberg-Marquardt learning algorithm in conjunction with the Quasi-Newton Broyden-Fletcher-Goldfarb-Shanno algorithm.

The data collected for this study consists of three input attributes and the target value (compressive strength of masonry wall). The statistical summary of the data collected is presented in Table 2.

3 Results

The comparison of various neural networks was done based on two parameters, coefficient of determination R^2 and root mean-squared error $RMSE$. Based on those results the most predestinated model for evaluating the compressive strength of masonry walls was selected as an artificial neural network with a structure consisting of 3 neurons in the input layer, 20 neurons in the hidden layer, and 1 neuron in the output layer, using the Levenberg-Marquardt learning algorithm. It is represented by the highest values of the coefficient of the determination equal to 0.987 for training, equal to 0.982 for testing and 0.988 for validation processes. It is also represented by the lowest values of the root mean-squared error equal to 1.36 for training, 1.71 for testing and 1.38 for validation. The results for this network, obtained for all of the processes: training, testing, and validation, are presented in Figure 3. They are shown as a relationship between the values obtained from experimental tests and those estimated using the artificial neural network.

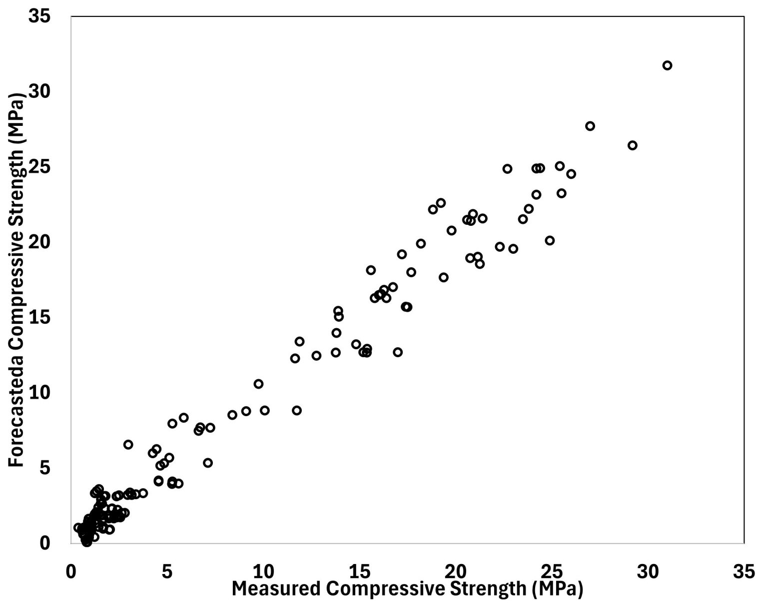

Figure 1: The relation between the compressive strength of masonry walls measured experimentally and evaluated using artificial network during training process

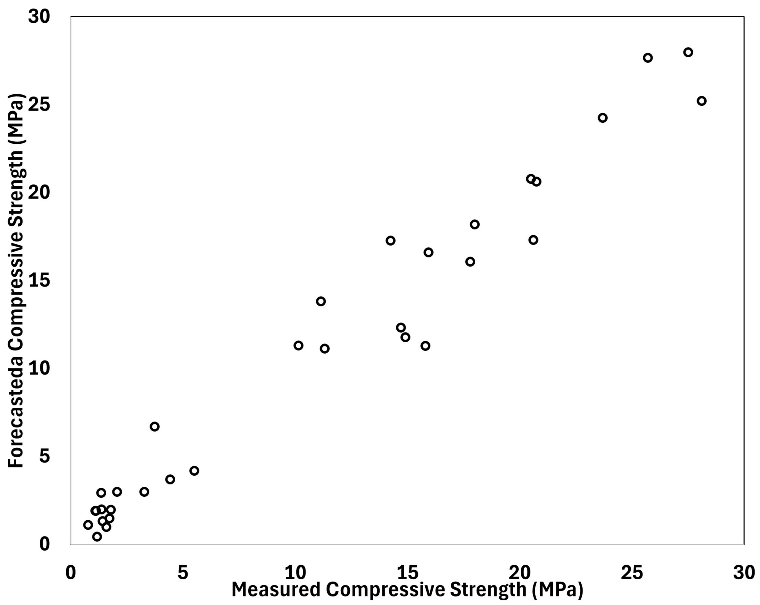

Figure 2: The relation between the compressive strength of masonry walls measured experimentally and evaluated using artificial network during testing process

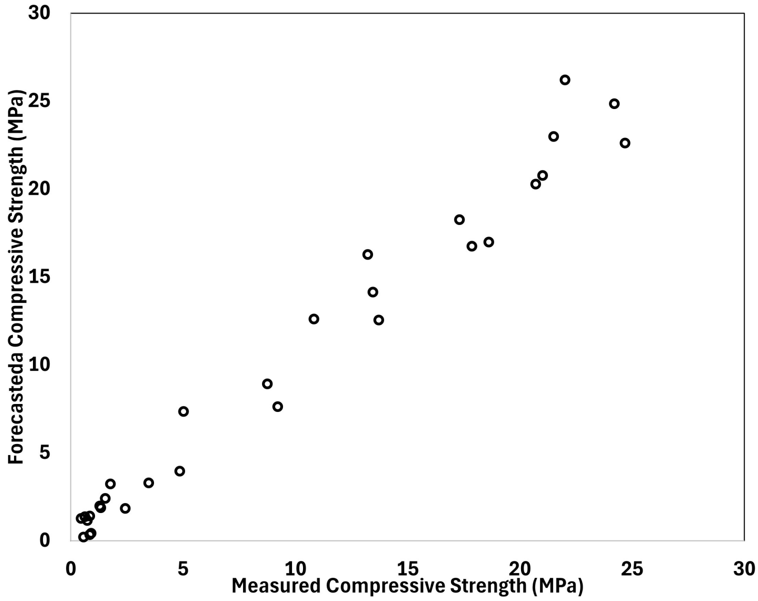

Figure 3: The relation between the compressive strength of masonry walls measured experimentally and evaluated using artificial network during validation process

4 Concluding remarks

This study successfully demonstrated the potential of machine learning techniques, specifically artificial neural networks (ANNs), for evaluating the compressive strength of masonry walls. By constructing a larger dataset for numerical analysis, the research provides a more comprehensive foundation for future studies and practical applications in this field. The selected model, an artificial neural network with 3 neurons in the input layer, 20 neurons in the hidden layer, and 1 neuron in the output layer, proved to be highly effective in predicting the compressive strength of masonry walls.

The results show that the ANN model, trained with the Levenberg-Marquardt learning algorithm, yielded excellent performance, with determination coefficients (R^2) of 0.987 for training, 0.982 for testing, and 0.988 for validation. Moreover, the model's root mean squared errors (RMSE) were minimal, with values of 1.36 for training, 1.71 for testing, and 1.38 for validation, highlighting the reliability of the model.

These results confirm the potential of machine learning methods, particularly ANNs, as a powerful tool for evaluating the structural performance of masonry walls. The integration of such models can significantly enhance the accuracy and efficiency of building design and construction processes. As the construction industry increasingly adopts AI and ML technologies, this approach has the potential to revolutionize the way masonry wall strength is assessed, contributing to the development of safer, more efficient, and cost-effective construction practices in the future.

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