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PREDICTING MASONRY WALL COMPRESSIVE STRENGTH USING ARTIFICIAL NEURAL NETWORKS

Abstract:

The application of artificial neural networks (ANNs) has significantly advanced the resolution of complex engineering problems in civil engineering, particularly in data analysis, design, and structural performance prediction. They play a crucial role in materials science by enabling the assessment of mechanical properties of construction materials and structural systems. This paper focuses on the use of ANNs for predicting the compressive strength of masonry walls, a key parameter for reliable structural design. The objective is to provide a systematic and critical review of relevant studies, highlighting the employed neural network models and their predictive accuracy compared to conventional approaches. The findings indicate that ANNs offer more reliable and accurate predictions of compressive strength, especially when experimental data are limited or heterogeneous, and support the development of auxiliary engineering tools and software applications.

Keywords: artificial intelligence, neural networks, compressive strength of masonry, masonry structures

ПРЕДВИЂАЊЕ ЧВРСТОЋЕ ПРИ ПРИТИСКУ ЗИДОВА ПРИМЕНОМ ВЕШТАЧКИХ НЕУРОНСКИХ МРЕЖА

Сажетак:

Примена вештачких неуронских мрежа (ANN) значајно је унапредила решавање сложених инжењерских проблема у грађевинарству, нарочито у областима анализе података, пројектовања и предвиђања понашања конструкција. Оне играју кључну улогу у науци о материјалима омогућавајући процену механичких својстава грађевинских материјала и структурних система. Овај рад се фокусира на употребу вештачких неуронских мрежа за предвиђање чврстоће на притисак зиданих зидова, што је кључни параметар за поуздано пројектовање конструкција. Циљ је пружити систематичан и критички преглед релевантних студија, истичући примењене моделе неуронских мрежа и њихову тачност предвиђања у поређењу са конвенционалним приступима. Налази указују на то да вештачке неуронске мреже нуде поузданија и прецизнија предвиђања чврстоће на притисак, нарочито када су експериментални подаци ограничени или хетерогени, и подржавају развој помоћних инжењерских алата и софтверских апликација.

Кључне ријечи: вештачка интелигенција, неуронске мреже, чврстоћа при притиску зида, зидане конструкције

1. INTRODUCTION

Masonry structures are among the oldest and most widely used structural systems in both historical and modern construction practice [1]. Their extensive application is attributed to material availability, simple construction techniques, and durability. However, their structural behavior is inherently complex due to the heterogeneous nature of masonry as a composite system. Since masonry walls are composed of masonry units and bonding materials with different mechanical and geometrical properties, defining their mechanical characteristics remains one of the fundamental and most challenging tasks in civil engineering [2]. The complexity is further increased by the large number of influencing parameters, including the properties of individual components, bonding pattern, unit geometry, and workmanship quality.

In structural design and decision-making processes, solving numerical problems is often time-consuming and computationally demanding. In recent years, artificial intelligence methods—particularly artificial neural networks (ANNs)—have been increasingly applied to civil engineering problems that are difficult to model accurately using conventional analytical approaches. ANNs, as a subset of machine learning techniques, enable the modeling of complex and nonlinear relationships between input and output variables based on experimental or numerical data, without requiring explicit formulation of analytical models.

Studies reported in the literature [3], [4], [5], [6] demonstrate that neural networks can achieve satisfactory, and frequently high, accuracy in various civil engineering applications, including prediction of material mechanical properties, estimation of structural capacity, optimization of design solutions, and analysis of structural behavior. Their application is especially significant in materials science, where they are used to estimate the mechanical properties of heterogeneous materials and structural systems.

Accurate knowledge of the mechanical properties of masonry walls is essential for reliable structural design. However, their determination is complicated by the interaction of numerous interdependent parameters. Existing approaches are largely based on empirical expressions, whose applicability is often limited and associated with considerable uncertainty, particularly in the absence of experimental testing [7]. Given that experimental determination of masonry compressive strength is complex, time-consuming, and costly, the use of artificial neural networks represents an efficient alternative for obtaining reliable estimates within a shorter time frame [8]. This paper presents a review and analysis of existing research on the application of neural networks for defining and predicting the compressive strength of masonry walls.

Accordingly, this paper systematically reviews the application of ANNs for predicting masonry compressive strength and evaluates their advantages over traditional approaches.

2. DETERMINATION OF THE COMPRESSIVE STRENGTH OF MASONRY WALLS

Masonry structures represent one of the oldest construction systems known to humankind. Owing to simple construction technology, material availability, and relatively low costs compared to modern structural systems, masonry structures still occupy an important position in contemporary engineering practice [9]. Their widespread use includes residential and public buildings, as well as a large stock of historical structures, further emphasizing the importance of reliable determination of their mechanical properties.

Masonry structures are composite systems whose mechanical behavior depends on numerous interrelated material, geometrical, and technological parameters. Since the constituent materials often exhibit non-uniform mechanical and geometrical characteristics, a masonry wall cannot be treated as a homogeneous structural element, but rather as a composite system characterized by pronounced heterogeneity and anisotropy. Due to this heterogeneity and anisotropy, defining mechanical properties—particularly compressive strength—remains a complex problem that has been addressed through various methodological approaches. Nevertheless, because of the interaction between masonry units and mortar, reliable determination of compressive strength remains a challenging task in engineering practice [10].

To date, there is no unified quantitative method that enables precise determination of masonry compressive strength solely on the basis of the mechanical and geometrical properties of its components. This is primarily due to the strongly nonlinear relationship between these parameters [9]. In general, methods for determining the compressive strength of masonry walls can be classified into experimental, empirical–analytical, and numerical–mechanical approaches, which form the basis for the development of modern artificial intelligence-based methods.

Experimental methods represent the reference and most reliable approach for determining masonry compressive strength. They are based on laboratory testing of specimens conducted in accordance with relevant standards and regulations [11], [12], [13], [14]. The result of experimental testing can be expressed in the functional form:

$$f_{c,w} = F(X) \tag{1}$$

where $f_{c,w}$ denotes the compressive strength of the masonry wall, and vector X represents a set of relevant parameters, such as the compressive strength of masonry units, mortar strength, geometrical characteristics of units and joints, and technological execution parameters. Although the experimental approach ensures high reliability, its practical application is often limited due to cost, time requirements, and the restricted number of tested configurations. Nevertheless, experimental data constitute the foundation for the development, calibration, and validation of all other methods.

Empirical–analytical methods were developed to formalize experimental results into simplified mathematical expressions suitable for engineering practice. These methods are widely adopted in current design codes [11] as well as in scientific research [16]. Depending on model complexity, empirical–analytical expressions may be classified as linear, power-law, and extended semi-empirical functions.

Linear models describe linear relationships between wall compressive strength and selected input parameters and can be generally written as:

$$f_{c,w} = a_0 + \sum_{i=1}^{n} a_i x_i \tag{2}$$

where x_i are relevant input parameters and a_i are empirical coefficients obtained through regression analysis of experimental data.

Power-law models represent the most frequently used empirical form in current masonry design standards. They assume a nonlinear power-type relationship between wall compressive strength and the mechanical properties of its components and can generally be expressed as:

$$f_{c,w} = \mathrm{K} \prod^{n} x_i^{a_i} \tag{3}$$

where K and α_i are empirical coefficients determined through statistical evaluation of experimental results.

In current masonry design standards [11], compressive strength is most commonly defined using empirical expressions. These expressions typically take the form of nonlinear power or product-type functions and can be written in general form as:

$$f_{c,w} = \mathrm{K} f_b^{\alpha} f_m^{\beta} \tag{4}$$

where f_b is the compressive strength of masonry units, f_m is the compressive strength of mortar, and K, α and β are empirical coefficients defined by the standard based on statistical analysis of experimental data. The values of these coefficients depend on the type of masonry units, mortar type, and bonding pattern.

The main advantage of code-based expressions lies in their simplicity and ease of application in engineering practice. However, their limitations are reflected in a relatively narrow range of applicability and the inability to account for a larger number of geometrical and technological parameters.

Extended semi-empirical models have been developed in scientific studies [16], [17] to incorporate a greater number of influencing parameters and provide a more accurate description of masonry behavior. These models often include geometrical ratios, workmanship quality parameters, and correction factors, and are mathematically formulated as nonlinear functions of more complex form:

$$f_{c,w} = g(x_1, x_2, \dots x_n) \tag{5}$$

where function $g(x_1, x_2, \dots x_n)$ may take exponential, logarithmic, or combined forms. Although these models frequently provide higher accuracy compared to standard code expressions, their applicability is generally limited to the materials and conditions for which they were calibrated.

In addition to code-based formulations, the literature contains numerous empirical and semi-empirical models [18] proposed by various researchers to achieve more accurate estimation of masonry compressive strength. These models often extend standard expressions by incorporating additional parameters such as geometrical characteristics of masonry units, joint thickness, wall height-to-thickness ratio, and workmanship quality. Mathematically, such models are typically formulated as nonlinear regression functions and can be written in general form as:

$$f_{c,w} = g\left(f_b, f_m, \frac{h}{b}, t_{j,\dots}\right) \tag{6}$$

where function g represents a nonlinear function calibrated using experimental data, while h/b and t_j denote geometrical parameters of the wall and mortar joint. In some studies, exponential, logarithmic, or combined functions are used to achieve better approximation of experimental results compared to standard expressions. Although these models may offer improved accuracy, their application is often restricted to specific wall types and materials, limiting their general applicability.

Numerical–mechanical methods, primarily based on the finite element method (FEM), enable detailed analysis of the mechanical behavior of masonry walls. In this approach, compressive strength is not a direct input parameter but rather a result obtained from numerical simulation of wall behavior under load. The material response is described by appropriate constitutive relations, which can be expressed in general form as:

$$\sigma = \mathrm{D}(\varepsilon)\varepsilon \tag{7}$$

where σ and ε are stress and strain vectors, and D represents the nonlinear material matrix. The reliability of numerical–mechanical methods largely depends on the accuracy of input material parameters, which are typically determined experimentally or through empirical expressions [19], [20]. Due to the requirement for detailed input data and high computational demand, the application of FEM in routine engineering practice is often limited, although it remains an essential research and verification tool.

Based on the above, experimental testing in accordance with relevant standards remains the most reliable method for determining masonry compressive strength. However, despite being the reference approach, its practical use is often constrained by high costs, time requirements, and the scope of laboratory testing. As an alternative, empirical–analytical methods derived from extensive experimental research are widely applied and successfully incorporated into modern masonry design codes. Numerical–mechanical methods, particularly FEM, enable more detailed analysis of masonry behavior.

Experimental, empirical–analytical, and numerical–mechanical approaches form the foundation of contemporary artificial intelligence-based methods. The results obtained using these approaches serve as databases for training and validating artificial neural network models. In this context, the application of artificial intelligence methods—especially artificial neural networks—represents a modern and promising approach to defining the compressive strength of masonry walls.

3. ARTIFICIAL NEURAL NETWORKS: THEORETICAL BACKGROUND

Artificial Neural Networks (ANNs) have attracted considerable attention in recent years across numerous scientific and engineering disciplines focused on data processing and complex problem solving [21]. Their significance lies in the ability to model complex, nonlinear relationships between input and output variables that are difficult or impossible to describe using conventional analytical or statistical methods. Owing to these characteristics, ANNs represent a typical interdisciplinary approach and have found extensive application in civil engineering.

Artificial neural networks are computational models inspired by the biological structure of the central nervous system. Their architecture consists of a large number of simple processing units—neurons—interconnected and organized within a network. Although they do not represent a direct biological replica, their operating principle resembles the way the human brain processes information through parallel signal processing and adaptive modification of inter-neuronal connections. For this reason, ANNs are often described as "black-box" models, in which the functional relationship between input and output is established through a learning process rather than explicit mathematical formulation. However, contemporary research demonstrates that, through proper validation, sensitivity analysis of input variables, and comparison with experimental data, a high level of reliability and engineering interpretability can be achieved.

A standard artificial neural network consists of three basic types of layers: an input layer, one or more hidden layers, and an output layer. Each neuron receives a set of input signals that are multiplied by corresponding synaptic weights, summed, and passed through an activation function. Mathematically, the neuron output can be expressed as:

$$y = f(\sum_{i=1}^{n} w_i x_i + b)_0 \tag{8}$$

where x_i are input variables, w_i are synaptic weights, b is the bias term, and f denotes the activation function [22]. The activation function introduces nonlinearity into the model and plays a key role in the network's ability to approximate complex functional relationships. Common activation functions include the sigmoid function, hyperbolic tangent (tanh), and ReLU (Rectified Linear Unit). Sigmoid and tanh functions are typically used in classical multilayer perceptron networks, while ReLU is predominantly applied in modern deep neural networks due to its favorable numerical properties and faster convergence during training.

Unlike classical algorithmic procedures, neural networks are not explicitly programmed to perform a predefined task; instead, they are trained using known datasets. The learning process is based on minimizing the error between the network output and the target output for a given set of input data. The most commonly used training algorithm for multilayer networks is backpropagation, in which synaptic weights are iteratively updated to minimize a selected loss function. Training continues until a satisfactory level of predictive accuracy is achieved.

The development of artificial neural networks can be divided into several characteristic periods. The first period began in the 1940s, when McCulloch and Pitts (1943) proposed the first mathematical model of a neuron, followed by Hebb (1949), who introduced a fundamental learning principle. The second period was marked by the development of the perceptron model, introduced by Rosenblatt (1958). Subsequent criticism by Minsky and Papert (1969) temporarily slowed progress in the field. The third period emerged with advances in computational technology and the introduction of the backpropagation algorithm by Werbos (1974), while Hopfield networks in the mid-1980s renewed scientific interest. A major milestone was the work of Rumelhart, Hinton, and Williams (1986), which established backpropagation as a practical and widely accepted training method. The fourth, contemporary period began in the early 1990s and is characterized by rapid development of learning algorithms and broad application of neural networks across engineering disciplines [22].

In civil engineering, the need to process large datasets and to define relationships among numerous interdependent variables makes ANNs particularly suitable tools. Their ability to operate with imprecise, incomplete, or noise-affected nonlinear and heterogeneous datasets enables successful application in areas such as construction materials, structural design, geomechanics, construction management, and decision-making processes [8]. Previous review studies indicate that neural networks often provide more reliable approximation of complex dependencies compared to classical theoretical approaches, especially in problems involving multiple interacting physical factors and where experimental data represent the primary source of information [6].

A significant advantage of ANNs in civil engineering lies in their ability to integrate experimental data of varying origin and quality, enabling modeling of structural and material behavior in situations where classical deterministic models provide limited accuracy. Accordingly, artificial neural networks can be considered an efficient and reliable tool for estimating the compressive strength of masonry walls, particularly when experimental data are limited, heterogeneous, or incomplete.

4. APPLICATION OF AI IN DEFINING THE COMPRESSIVE STRENGTH OF MASONRY STRUCTURES

The design of masonry structures has historically relied heavily on engineers' experiential knowledge, with structural behavior primarily formulated through empirical rules rather than within a rigorous scientific framework [2]. Understanding the mechanical properties of materials and the response of masonry structures was largely based on intuitive reasoning, where engineering knowledge remained implicit and experience-driven. In this context, a clear parallel can be drawn with the modern concept of artificial neural networks, whose application enables the formalization, storage, and transfer of engineering knowledge in a mathematically defined form.

With the rapid development of artificial neural networks, their application in civil engineering—particularly in materials science—has become increasingly prominent. ANNs allow the development of predictive models directly from available experimental data, without requiring predefined constitutive relationships. In this manner, the classical analytical description of materials can be replaced by a properly trained neural network capable of implicitly identifying the governing relationships of the modeled problem.

Studies reported in the literature (Table 1) confirm that artificial neural networks achieve high accuracy in predicting the compressive strength of masonry walls, often demonstrating better agreement with experimental results compared to conventional empirical expressions. Notably, neural networks have shown reliable predictive capability even when limited input data are available, highlighting their potential as efficient engineering tools for estimating masonry compressive strength.

Analysis of the studies summarized in Table 1 indicates that the application of neural networks follows a common conceptual framework, regardless of wall type, material characteristics, or dataset size. This framework is fundamentally based on previously conducted experimental investigations, whose results form the database used for network development and training.

Table 1. Overview of studies in which AI was applied to determine compressive strength

Authors	Number of Data Points	Input Parameters	ANN Architecture	Comparison with Empirical/Code-Based Methods	Conclusion
Garzón-Roca et al. [24]	96	f_b, f_m	2–5–1	EC6, ACI, Mann, Kaushik, Dimiotis	ANN shows better agreement; empirical models deviate by ≈20%
Zhou et al. [25]	102	f_b, f_m, h/t	3–12–1	TMS 402, CSA S304.1, EC6	Empirical models underestimate by ≈20%; ANN close to experimental results
Asteris et al. [9]	232	f_b, f_m, h/t, VF_b, VR_mH	3–8–28–1	Multiple empirical expressions	ANN reliably and efficiently predicts compressive strength
Carozza & Cimmino [26]	30	f_b, f_m, material type	5–3–5–1	Empirical formulas	ANN yields lower SSE and better accuracy even with a small dataset
Alotaibi & Galal [1]	326	f_b, h/t, C	3–10–1	7 empirical models	ANN shows the best agreement with experimental results
Muthukumar & Jegatheeswaran [10]	>120	f_b, fm, h/t	3–1–12–1	3 empirical models	Empirical models underestimate by ≈18%; ANN close to experimental results

In a typical modeling procedure, the input parameters of the neural network include mechanical properties of masonry units and mortar, as well as geometrical characteristics of the wall. The most frequently used input variables are the compressive strength of masonry units (f_b), compressive strength of mortar (f_m), and the wall height-to-thickness ratio (h/t). More advanced models also consider additional parameters such as volumetric proportions of units and mortar, wall type, and correction coefficients accounting for material heterogeneity.

The training process is most commonly implemented using multilayer perceptron feedforward networks combined with the backpropagation algorithm. In most studies, the available database is divided into training, validation, and testing subsets, with approximately 70–80% of the data allocated for training and the remainder used for validation and testing. This proportion has been widely reported as suitable for achieving stable and reliable predictive models.

5. ADVANTAGES OF AI OVER CONVENTIONAL APPROACHES

The analysis of the reviewed studies clearly indicates that artificial neural networks achieve significantly better agreement with experimental results compared to classical empirical expressions and models incorporated in current masonry design codes. In nearly all analyzed studies, empirical models—including those adopted in standards—demonstrate a tendency to underestimate the compressive strength of masonry walls, with average deviations typically ranging from approximately 18% to 25%.

The primary reason for this behavior lies in the fact that empirical and semi-empirical models are generally based on simplified functional relationships, most commonly of linear or power-law form. Such formulations are inherently limited in their ability to capture the nonlinear and interdependent effects of multiple input parameters influencing the mechanical behavior of masonry walls. In contrast, artificial neural networks implicitly model complex nonlinear relationships between input and output variables without requiring a predefined mathematical expression. This capability becomes particularly relevant when dealing with heterogeneous datasets that include different masonry unit types, mortar properties, and geometrical configurations, where conventional models often exhibit substantial limitations.

It is particularly noteworthy that several studies report reliable predictive performance even when relatively small experimental datasets were available. This finding highlights the ability of neural networks to generalize system behavior under conditions of limited training data. Such capability is of considerable importance in engineering practice, where experimental data are frequently fragmented or incomplete.

Based on the presented results, artificial neural networks can be considered an efficient and reliable tool for estimating the compressive strength of masonry walls, especially in situations where laboratory testing is unavailable or economically impractical. Their application creates opportunities for the development of auxiliary engineering tools and software applications that may support preliminary design phases and the assessment of the load-bearing capacity of existing structures.

However, it is important to emphasize that artificial neural networks should not be viewed as a replacement for experimental testing or existing design codes, but rather as a complementary approach. Experimental investigations provide reference values and a physical basis for understanding the problem, while empirical and numerical models contribute to identifying dominant parameters and their influence on compressive strength. Artificial neural networks integrate these sources of knowledge into a unified predictive framework, potentially overcoming the limitations of individual methods. Future research should focus on standardizing input parameters, expanding and improving database quality, and developing hybrid models that combine physically based mechanical formulations with artificial intelligence techniques.

6. CONCLUSION

This study presents a systematic review and analysis of contemporary approaches for determining the compressive strength of masonry walls, with a particular focus on the application of artificial neural networks as an artificial intelligence tool. It has been demonstrated that defining the mechanical properties of masonry structures, especially wall compressive strength, represents a complex engineering challenge due to the pronounced heterogeneity and nonlinear behavior of the composite formed by masonry units and mortar.

Analysis of experimental, empirical-analytical, and numerical-mechanical methods indicates that conventional approaches—including those embedded in current design codes—rely heavily on simplified mathematical expressions, most commonly linear or power-law functions, which fail to fully capture the interdependence of multiple input parameters. Consequently, a consistent trend of underestimating masonry compressive strength relative to experimental results has been observed.

In contrast, the reviewed studies clearly show that artificial neural networks provide more reliable and accurate predictions of masonry wall compressive strength. Their advantage lies in the ability to implicitly model complex nonlinear relationships between the mechanical and geometrical characteristics of the wall's constituent components, without the need for a predefined functional relationship. In most cases, neural network predictions demonstrate significantly better agreement with experimental data compared to empirical models and code-based expressions.

Based on the analysis, it can be concluded that artificial neural networks serve as an effective complementary tool for estimating the compressive strength of masonry structures, particularly when laboratory testing is limited or unavailable. Their application does not replace experimental methods or established design codes but enhances them, enabling more informed engineering decision-making during the design and assessment of masonry structures.

Future research should aim at hybrid AI-mechanical models, larger datasets, and standardization of input parameters to further improve predictive accuracy.

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