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Партизански одреди 24, П. Фах 560, 1000 Скопје
Северна Македонија

MASE
MACEDONIAN ASSOCIATION OF STRUCTURAL ENGINEERS
Partizanski odredi 24, P. Box 560, 1000 Skopje
North Macedonia

AI-6

mase@gf.ukim.edu.mk
http://mase.gf.ukim.edu.mk

ARTIFICIAL NEURAL NETWORKS AND THEIR APPLICATION IN THE DESIGN OF MASONRY STRUCTURES

Žarko PETROVIĆ [1] Bojan MILOŠEVIĆ[2], Nenad KOJIĆ [3]

ABSTRACT

Masonry structures are widely used thanks to the variety of materials used for their construction. Calculating their load-bearing capacity is complex because walls are composite materials with an inhomogeneous and anisotropic nature. As masonry structures are exposed to different types of loads, accurate determination of load bearing capacity is a key aspect in the design and reconstruction phases, which represents a major design challenge to ensure the safety and efficiency of the structure. Artificial neural networks (ANN) are increasingly being used to solve engineering problems, including data analysis, decision making, optimization, and structural response prediction. Their application in civil engineering allows for a more accurate and faster load analysis compared to traditional methods. This paper aims to present the existing research in literature dealing with the application of ANN in the calculation of the bearing capacity of masonry structures, analyzing their advantages and possibilities in the optimization of design solutions.

Keywords: Artificial neural networks (ANN); Masonry structures; Load-bearing capacity

[1] Faculty of Civil Engineering and Architecture of the University of Niš, Serbia

Corresponding author: Žarko PETROVIĆ, e-mail: zarko.petrovic@gaf.ni.ac.rs
[2] Faculty of Mechanical Engineering and Civil Engineering in Kraljevo of the University of Kragujevac, Serbia
[3] Academy of technical and art applied studies, Department of Information and Communication Technologies, Belgrade, Serbia

1. INTRODUCTION

Masonry structures are among the oldest and most widely used building systems, present in both historical and modern architecture, especially in high-rise buildings. Their widespread use has resulted from the availability of a variety of materials used for masonry, including various types of masonry elements and binders. A key aspect in the analysis of these constructions is the determination of their mechanical properties and load capacity, which is complicated by their complex structure and specific behavior under load.

The materials used in masonry are characterized by an inhomogeneous and anisotropic structure, which further complicates the calculation of load bearing capacity. Therefore, advanced analytical methods are needed to precisely define the resistance and behavior of walls in different exploitation conditions. Traditional calculations, which rely on empirical formulas and numerical simulations, are often not flexible enough to include all the factors that influence the behavior of these structures.

The design of masonry structures is an iterative process in which the load bearing capacity and resistance of the system is optimized through a series of calculations and simulations. This process requires significant resources, expertise and time to ensure the structure complies with building regulations and safety standards. Conventional methods, such as the Finite Element Method (FEM), allow precise analysis, but are very demanding in terms of computational processing and execution time.

In order to reduce the costs and time required for analysis, an increasing amount of research is directed towards the application of artificial intelligence in solving the problems of building constructions. Neural networks have shown potential for reliable analysis of the load-bearing capacity of walls, enabling more accurate calculations with less computational complexity. Studies have shown that ANN models can be used to predict load capacities with high accuracy, providing engineers with a tool for faster and more efficient design.

This paper aims to review scientific research on ANN applications in masonry structures dealing with the application of neural networks in determining the bearing capacity of masonry structures under different types of loads. This paper reviews the advantages, challenges, and potential applications of ANN models for optimizing masonry structure designs.

2. MASONRY STRUCTURES

Masonry structures must be designed, calculated and executed in such a way as to provide an adequate response to all types of loads and external influences. These systems consist of masonry elements connected by a binder material, which gives them complex, often non-linear behavior under load. The mechanical properties of walls are affected by geometric and material characteristics, the arrangement of elements and the presence of openings, which makes it difficult to precisely define their structural capabilities [1].

Different types of masonry constructions, such as classic, cerclage-framed and reinforced walls, have specific calculation criteria. They are most often exposed to axial forces, but it is crucial to analyze their resistance both in the plane and perpendicular to the plane of the wall, especially in the case of dynamic loads such as seismic forces. Assessing the load-bearing capacity depends on the geometry of the wall, eccentricity of the load and interaction with other structural elements.

While FEM provides detailed stress distribution analysis, its computational demands make it impractical for real-time or large-scale parametric studies. ANN models can approximate these responses more efficiently in some cases, though they require extensive training data. The large number of elements required for accurate simulations further complicates its practical application, making the process time-consuming and expensive.

In addition to the design of new structures, it is also important to examine damaged buildings. Various rehabilitation techniques, such as resin injection, reinforced mortars and FRP systems, are applied to improve the load bearing capacity. Experimental tests are often expensive, so numerical methods are used to assess the reliability of these techniques, providing a more efficient approach to rebuilding and strengthening walls.

3. DEVELOPMENT OF ANN AND THEIR APPLICATION IN CIVIL ENGINEERING

Artificial Neural Networks have become a key tool in the field of artificial intelligence in recent years, thanks to their ability to manage large amounts of data and solve complex engineering problems. Their application spans various scientific disciplines, including civil engineering, where they have proven to be a useful alternative to traditional methods of analysis and design.

The first applications of ANN in civil engineering date back to the 1990s, when they were used to model structures. During the last decade, ANN models have been successfully used to analyze soil behavior, estimate the load bearing capacity of foundations, stability of retaining walls and tunnel structures [2,3]. Their application in civil engineering enables better data management and more accurate predictions compared to standard statistical methods.

ANN are inspired by the structure of the human brain and consist of interconnected nodes (neurons) organized in layers. Their main advantage is the ability to learn from data and recognize patterns that are not obvious through classical methods. A key step in their implementation is the preparation of an adequate data set, which must be representative and large enough to allow the network to generate accurate results. The training of the ANN takes place through an iterative process in which the output results are compared with the actual values, and the system adjusts the weights of the connections between the neurons to minimize the error. By using different activation functions, such as sigmoid and ReLU (Rectified Linear Unit), networks can simulate nonlinear processes, which makes them suitable for construction problems where the relationships between variables are complex [4,5,6].

The application of ANN in construction has shown particularly good results in geomechanics and materials science, design optimization, analysis of mechanical properties of materials where traditional numerical methods are often limited. Thanks to their flexibility, ANN enable the improvement of predictions without the need for predefined mathematical models. Compared to classical numerical methods, ANN offer a more efficient solution to problems where it is difficult to formulate exact mathematical expressions. Their ability to learn from data makes them a valuable tool in structural engineering, particularly for load-bearing capacity assessment in cases where traditional methods are computationally expensive or insufficiently flexible and optimization of design solutions.

4. ANN APPLICATIONS IN DEFINING THE LOAD BEARING CAPACITY OF MASONRY STRUCTURES

In the past, engineering knowledge was primarily stored in experts' minds, and the behavior of masonry structures was largely understood through intuition [1]. If we draw a parallel with ANN, one can come to the conclusion that their application in construction will enable the transfer of knowledge, which this time is precisely defined. In this part of the paper, the use of artificial neural networks in the field of masonry constructions, as well as models of artificial neural networks used for structural design and calculation of masonry constructions, is presented.

Garzón-Roc et al. (2013) investigated ANN applications by conducting 3696 simulations [7] in which the modified values of load eccentricity, wall’s slenderness ratio and structural stiffness formed ANN for determining the axial load of a solid brick masonry wall with cement mortar. Three different ANNs were developed with one hidden layer in which the number of neurons is variable, with an input layer in which the three neurons are the parameter load eccentricity, lambda coefficient and masonry tensil to compressive strength ratio and with an output layer that defines the load reduction coefficient. The input and output layers contained linear neurons, while the sigmoid function was used as a transfer function in the hidden layer. The obtained results agree with Eurocode 6 and other experimental studies.

Using an ANN with a backpropagation algorithm. Zhang Y. et al. [8] predicting the fracture of a wall exposed to a vertical load. The experimental data contained a total of 88 wall samples made of grouted concrete blocks. The network in the input layer has four neurons, one hidden layer and one output layer with one neuron that defines the value of the force under which the crack in the wall occurs. This artificial neural network based on CA numerical model in which von Neumann and Moore model are embedded can accurately predict the cracking model of masonry walls.

Urbański A., Ligęza, S., Drabczyk I. M. [9] presented a method of creating a constitutive model for modeling masonry structures using FEM with a one-way ANN driver of the multi-layer perceptron type implemented in the finite element as a constitutive function. The ANN had one hidden layer with sixteen neurons, while the ReLU activation function was applied. It is possible to model masonry walls subjected not only to axial loads, but also to bending moments. In this paper, an elastic-perfectly plastic model was considered, so the appearance of cracks was neglected, while the improvement of the model would require a proper description of the damage and the display of yielding in the material, which is expected to be automatically simulated by that ANN.

Friaa, H et al. [10] in their paper investigate the development of an ANN model to predict the properties of an equivalent Love-Kirchhoff plate of hollow block wall mainly based on material and geometrical parameters. A multi-layer perceptron neural network was designed and trained using the back-propagation algorithm. The constructed network model (ANN 5-14-8) has three layers of neurons, the input layer contains five neurons representing five main material and geometric input parameters, one hidden layer with fourteen neurons, while the number of output neurons is eight and consists of different homogenized coefficients of equivalent plates of masonry hollow concrete blocks of the wall. A sigmoid activation function is applied in the hidden layer. Compared to the results of FEM calculations, the developed algorithm is faster than FEM simulation, with high accuracy and precision.

In their work, Mathew A. et al. [11] analyze masonry walls subjected to biaxial bending, using a hybrid system that combines the capabilities of ANN and CBR to predict the pressure at which wall failure occurs. A multi-layer feedforward neural network with a feedback algorithm and a sigmoid activation function was used. The number of nodes in the input layer is equal to the number of inputs used to represent the problem (physical properties such as length, aspect ratio, and the section modulus of the panel and its mechanical properties such as flexural strength in a stronger direction and the orthotropic strength and stiffness ratios), the output layer consisted of one output node, the pressure force that leads to failure, while the hidden layer contained six neurons. Walls with eight different boundary conditions were considered, the results were compared with the results obtained using FEM. The presented hybrid system successfully predicts the failure pressure of masonry panels subjected to biaxial bending with various boundary conditions.

In their study, Khaleghi M. et al. [12] following the results of the verified Multi-Per MP method, an artificial neural network (ANN) was trained aiming to develop an innovative empirical approach to predict the load capacity and initial stiffness of a perforated unreinforced UMV wall. Based on a database of 49 unreinforced walls with different openings and proportions, the input data is a function of the ratio of the height of the opening to the height of the wall and the width of the opening to the width of the wall, while the output represents the load bearing capacity and stiffness of the wall. A network with one hidden layer containing seven neurons has the best performance for predicting the load bearing capacity and stiffness of a perforated masonry wall with a central opening. The Levenberg-Marquardt (LM) algorithm was used to train the network, while tansig and purlin were chosen for the activation functions in the output and hidden layers, respectively.

The work of Zhou G. et al. [13] presents an innovative technique and combines cellular automata (CA) with ANN to predict the failure load and failure mode of laterally loaded walls. The input data is the wall failure pattern obtained by applying the CA model, and the output data is the intensity of the load that leads to the failure. The network also had one hidden layer with 6 neurons after verification of 1, 2 and 3 hidden layers with 6, 12 and 18 cells respectively, while the network was trained using the backpropagation (BP) algorithm. Experimental results as well as those obtained using the finite element method were used to train the network. ANN is able to predict failure load more accurately than FEA technique can, so AI technique can replace conventional techniques for predicting failure load and wall failure patterns.

Zhou G. et al [14] deals with the application of artificial intelligence to predict the failure/crack loads of laterally loaded masonry walls based on their corresponding failure/crack patterns obtained from experimental data. In order to establish the relationship between the failure pattern and the wall failure load, three network models, backpropagation BP, radial basis function RBF, and resource allocation network RAN were considered. The BP neural network model consists of a 32 x 1 input layer, which is used to input failure/crack patterns on the masonry wall of various configurations, a hidden layer, and a single neuron output layer used to define the masonry wall load based on the failure/crack model. Based on the accuracy, the RBF and RA network models could be more stable and reliable than the BP network in this prediction task, and in addition, the RBF and RA network models require less training time than the BP network model.

T. M. Ferreira, et al. were involved in the assessment of the seismic sensitivity of masonry structures using ANN [15] and not only to obtain a solution to the problem, but to develop a new simplified expression of the degree of damage. The expression that best fits the results is obtained by applying a multi-layer neural network with an advanced flow backpropagation algorithm for 90 stone buildings of a certain degree of damage, which are classified according to the European Macroseismic Scale, EMS-98. MFFNN consists of two artificial neurons in the input layer, 16 neurons in one hidden layer, and one neuron in the output layer. As the original formulation for damage assessment in masonry buildings resembles a sigmoid function, a sigmoid function was applied to train the network. The presented analytical sensitivity function provides a better fit to the observed damage than that defined based on the traditional formulation of the degree of damage.

The aim of Pillac J. C. S. et al. paper [16] is the application of ANN in the design of masonry walls framed by cerclages. For the training network, 33 models of four-story buildings with dimensions from 12 m to 25 m in one direction and 6 m to 12 m in the other direction were used. Each of these values represents a neuron in the input layer. The output values are the dimensions of the construction elements such as; vertical and horizontal cerclages, lintels, as well as the diameter and number of stirrups and longitudinal reinforcement for each of these elements, resulting in 26 neurons in the output layer of the network. ANN training is carried out using the backpropagation algorithm, where a tangential sigmoid activation function is applied in the hidden layer and a linear function in the output layer. Artificial neural networks can be used to design cerclage-framed masonry structures with a 10% margin of error compared to traditional designs, while reducing design time and cost.

The response of FRP-strengthened masonry under seismic loading was considered by Dihoru L. et al [17]. The source for training and testing the neural network is experimental tests and results from 64 records of structural responses with four reinforcement methods. The architecture of the artificial neural network is 12 inputs (seismic soil parameters and wall characteristics), 2 outputs (wall displacement and velocity), 3 hidden layers of 8 neurons each and one output layer, and the transfer function used in the inner layers was a tangential sigmoid function. Standard back-propagation with gradient descent algorithm was used in training. Since the ANN training included both elastic and plastic response data, the prediction proved to be satisfactory for both unreinforced URM walls and FRP-reinforced walls.

Ferrario E. et al. [18] used an ANN to approximate the nonlinear seismic response of a masonry building. The influence of the soil on the seismic response of a two-story masonry structure on a shallow foundation was investigated, simulated on the basis of nonlinear dynamic analysis using the finite element method, based on 168 recorded accelerograms from the database of the Pacific Earthquake Engineering Research Center (PEER). The proposed network takes into account load eccentricity, the ratio of wall slenderness to stiffness and wall tensile strength, and has been verified by comparison with Eurocode 6 and other regulations, as well as with three experimental studies. Through this research, the possibility of replacing the FEM with a fast regression model was examined, i.e. ANN, and the results showed a satisfactory ability of ANN to approximate the FEM output in less than a second.

Also, Ferrario E. et al. [19] show the approach on a case study of seismic risk assessment involving the estimation of the fragility curves for a masonry structure. The neural network was trained, validated and tested considering 13 previously defined input data, while the number of hidden nodes identified by the algorithm was 5. The ANN showed a good ability to approximate the FEM output. It can be seen that the interpolation capabilities of the metamodel increase by reducing the number of inputs so, at the end of the analysis, five inputs have been selected (Arias intensity, spectral acceleration at the first-mode period of the structure, mean period, predominant period, spectral intensity). The capability of the ANN to provide results similar to the FEM has been confirmed by the comparison between the fragility curves obtained by the two methods on the test data set.

In their paper, Zhou Q. [20] deal with the prediction of shear strength and shear capacity of masonry walls made of grouted reinforced concrete blocks (RCBM), using ANN, and based on the results of 84 experimental test data. Eleven main parameters are considered as input parameters: compressive strength of the grouted concrete block wall, wall height, wall length, wall thickness, effective wall length, axial load, longitudinal and transverse reinforcement ratios, horizontal spacing of reinforcement and yield strength, longitudinal and transverse reinforcement. In addition to eleven input data, the proposed model has one output parameter and one hidden layer with fifteen neurons. A nonlinear sigmoid activation function was used in the hidden layer, while a linear activation function was used in the output layer. An advanced training algorithm with Bayesian Regularization based on the Levenberg-Marquardt backpropagation algorithm was used for network training instead of the standard BP algorithm. The results of the ANN model agree well with the experimental values and the tested models are compared with the existing standards MSJC, SANZ 2004, CSA S304.1 and GB50003, as well as the models proposed by Shing and Matsumura.

An analytical model based on an ANN was proposed and discussed by Cascardi A.. Micelli, F.. Aiello M.A. [21] in terms of geometrical and mechanical parameters that define the mechanical problem and are able to predict the shear resistance of FRM reinforced wall. The network consists of three layers, an input layer with 2 nodes representing 4 mechanical properties and 2 geometrical information of the multilayer wall, three hidden layers with 10 neurons and one neuron in the output layer. The network was formed on the basis of a database of 113 samples with the same configuration of reinforcement, test setup and different failure types. Based on the comparison of the results with the relevant international regulations for the design of masonry structures, it was observed that the proposed model is competitive with analytical formulations.

Gopinath, S., Kumar A. [22] performed cross-sectional analysis and prediction of flexural capacity of textile strengthened masonry walls. A back-propagation neural network consisting of several interconnected artificial neurons is applied, using a gradient descent approach to minimize the error function. The network consists of an input layer with four neurons, an output layer with two neurons, as well as four hidden layers. Experimental data were used for 29 different types of TRM, which were shown in the research conducted so far. The ANN-based model is able to predict both the tensile strength and effectiveness of wall reinforcement textiles very reliably.

The effect of the explosion as an incident load was dealt with by Thango S. G. et al [23] using an ANN that was trained on the basis of 95 numerical simulations using the finite element method. In the study, a multi-layer neural network was used, which had two neurons at the input, the weight of the explosive and the distance, ten neurons in the hidden layer and one neuron in the output layer representing the deformation of the wall. The function during network training was performed using Levenberg-Marquardt backpropagation (TRAINLM) and it was found that limited results were achieved in the application of artificial intelligence in the effect of an explosion on an object.

The paper of Mavrouli O. et al. [24] deals with damage to masonry walls that are subjected to stone impacts due to the most common ground movement and rock fall. The created database on the basis of which the ANN was formed contained 672 sets of data obtained by applying the finite element method. Four input parameters, two of which characterize the masonry wall (wall width and tensile strength) and two the kinematics of the stone block (volume and speed of the stone block), while the damage index (DI) is determined as the output parameter. Forms of neural networks with different transfer functions were investigated. In order to optimally estimate the expected wall damage, the ANN LM 4-21-1 model was selected, in which the normalized radial base transfer function (NRB) was used for the input layer and the Hyperbolic Tangent Sigmoid Transfer Function (HTS) for the output layer. The analytical expression obtained based on the ANN LM 4-21-1 model can be used to estimate the damage index of the masonry wall.

Bakas I., Kontoleon K. J. [25] propose a neural network capable of predicting the temperature development on the unexposed side of a masonry wall over time, based on the standard fire curve (Eurocode EN1991-1-2). During the research, four models of neural networks, multilayer perceptron (MLP) were formed. The number of input and output nodes is defined by the number of input and output variables, respectively. The input layer has 8 nodes, which reflect the number of input variables. The output layer includes one node representing the dependent variable, which the ANN must predict (the temperature of the unexposed wall surface over time). Two hidden layers as well as linear activation unit used in both hidden layers of all models. The focus of this paper is to identify the impact of different amounts and quality of input data on the accuracy of a specific ANN architecture. The general mechanism of the heat transfer process using the ANN is captured, as indicated by the fact that the basic prediction curves are approximately parallel, with the ANN managing to predict the final temperature developed on the unexposed surface of the wall test specimens with a relatively small error.

5. CONCLUSIONS

Based on the conducted analysis, it can be concluded that the application of ANN in the calculation of masonry structures has significant potential, but requires careful selection of methods and optimization of model parameters. ANN-based prediction models, hybrid approaches, and metamodels enable faster and more accurate load capacity and structural damage analysis compared to traditional methods. However, their success depends on the quality of the available data and the correct implementation of the model.

All the analyzed papers show that for different types of observed problems, different forms of ANN must be used, and additionally the topology of the network itself must be adjusted. Tolology primarily refers to the number of hidden layers, the number of neurons in the layers, but also the use of an appropriate activation function and error detection methodology. The results also show that the obtained predictions have a high predictive accuracy and expert reliability, which is only a support for expert persons for further decision-making, but that the result is directly correlated with the number of available inputs for ANN training.

Further development of this area can contribute to more precise design of masonry structures, as well as improvement of existing standards in civil engineering.

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