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Overview of the application of Artificial Neural Networks in the determination of some mechanical characteristics of masonry walls

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ABSTRACT

Artificial intelligence (AI) has found wide application in solving many problems in engineering and also in construction, where its application is primarily reflected in faster and simpler solving of calculation problems. Artificial Neural Networks (ANN), as a method of artificial intelligence, are applied in the problems of construction design, management when making decisions, data analysis, design, optimization and prediction of construction responses. In the design phase of masonry structures, one of the main tasks is to adequately define the mechanical characteristics of the wall as a basis for quality design. The aim of this paper is to present and analyze the scientific results of the application of ANN in the determination of some of the mechanical characteristics of the walls in masonry constructions.

KEYWORDS

Artificial neural networks, Masonry structures, Compressive strength, Creep, Biaxial failure.

1. INTRODUCTION

Masonry structures and the materials used for their construction represent the oldest and most widespread types of structures in both historical and modern buildings [1]. As in the process of masonry and the formation of structural elements, masonry elements and binders from different materials are used, defining the mechanical characteristics of masonry structures is one of the basic and challenging issues in designing [2].

In recent years, the application of AI in solving construction problems that are difficult to solve using conventional engineering approaches has been expressed. Artificial Neural Networks (ANN) are computational models inspired by the structure and functioning of the human brain. Their primary role is the processing of complex data, pattern recognition, and prediction of system behavior, especially in situations where it is difficult or impossible to define mathematical relationships using conventional methods. Consequently, ANN have found increasingly widespread application in the field of civil engineering over the past decade, both in structural design and in predicting the mechanical properties of materials, optimizing processes, and simulating complex physical phenomena. In this paper, special attention is devoted to the analysis of the application of ANN in the process of defining the mechanical characteristics of masonry structures. Conducted research [3-11] showed that the application of ANNs can provide appropriate accuracy when solving some problems in construction engineering and is an effective tool for the formation of useful applications.

As defining the mechanical characteristics of walls is necessary for the adequate design of masonry structures, efforts have been made so far to determine these characteristics using empirical expressions, although it can be said that it is still very questionable in the absence of laboratory tests [3]. On the other hand, as the laboratory determination of mechanical characteristics is a demanding and extensive process, the application of AI often provides adequate solutions that are obtained in a fast and efficient way [7]. The aim of this paper is to present an overview and perform an analysis of ANNs applied so far, which are used to determine some of the mechanical characteristics of masonry walls.

2. MASONRY STRUCTURES AND THEIR MECHANICAL CHARACTERISTIC

Masonry systems are one of the oldest building construction systems known to mankind. Due to its simple construction, low prices compared to other modern construction materials, masonry structures are still one of the most widespread construction systems [12]. Walls as structural elements represent a composite element obtained by joining together structural elements - masonry elements with a suitable binder. When forming walls, a large range of arrangement of masonry elements as well as their geometrical characteristics can be observed, whereby different types of binding agent can be used [13]. Knowledge of the mechanical characteristics of the walls of masonry constructions largely depends on the mechanical characteristics of the applied masonry elements as well as the characteristics of the applied binding material. The mechanical characteristics of the applied materials can often be inconsistent, so it is best to apply appropriate laboratory methods to define the mechanical characteristics of masonry structures.

Masonry structures represent an important part of the cultural and historical heritage and identity of the areas where they are located, where religious buildings, certain fortifications or cultural monuments are most often included here. In the case of these buildings, defining the mechanical characteristics of the walls is a rather complex process, which in most cases also requires the application of certain experimental methods. Defining the exact mechanical characteristics of the walls of historical buildings is important for defining the response of the structure under the effect of different loads, especially because the structural components are composite structures [14]. When it comes to the creation of new masonry systems, defining the mechanical characteristics of the walls is possible by applying experimental methods or appropriate empirical expressions that are often integral parts of the valid regulations for the construction of masonry structures. In both cases, knowledge of the mechanical characteristics is necessary for the formation of adequate models of the masonry structure and its calculation, usually using the finite element method (FEM).

Defining and knowing the mechanical characteristics of masonry structures includes the knowledge of bulk weight, Young's modulus of elasticity, Poisson's ratio, compressive strength, tensile strength, yield strength etc. which knowledge is necessary to simulate the actual behavior of masonry structures [13]. In addition to the mechanical characteristics of masonry elements and binders, the mechanical characteristics of the wall are also influenced by the geometric characteristics of the masonry elements, i.e. the ratio of the height and width of the elements used for masonry, so that the determination of the mechanical characteristics of the walls of masonry structures is very complex precisely because of the inhomogeneous and anisotropic nature of these structures [12].

The key parameter for adequate design and analysis of the response of the masonry structure is the compressive strength of the masonry structure, the determination of which is sometimes a complex problem [15]. It can be said that currently there is no quantitative method that would reliably determine the compressive strength of a wall based on the mechanical and geometric characteristics of its constituent components, which is a consequence of the highly non-linear relationship between the compressive strength of the wall and the geometric and mechanical characteristics of the constituent components of the wall [12]. For the purposes of designing and building buildings in the masonry system, it is most authoritative to define the necessary mechanical characteristics based on the applied materials experimentally based on valid standards, although they can also be defined on the basis of empirical expressions defined in the standards.

When masonry walls are exposed to the effect of a uniform load, it can be said that a complex stress state occurs in them. This is a consequence of the application of inhomogeneous materials, the thickness of the applied mortar, the presence of voids in the mortar joints, uneven compaction and the absorption of water from the mortar during the setting process. As masonry walls are composite materials, characterized by extremely brittle and anisotropic behavior, the realization of a reliable experimental test is very difficult, expensive and complicated, under conditions of both uniaxial and biaxial stress. In addition, many researchers have conducted experimental tests on masonry walls in order to define their failure mode.

Researchers have long been aware of the importance of the angle at which the load is applied to the masonry wall relative to the mortar joint, so a large number of experimental tests have aimed to produce indirect tensile stresses at joints that are at different angles to the vertical load. Depending on the orientation of the mortar joints according to the direction of stress, failure can occur only in the mortar joints or simultaneously in the mortar joints and masonry elements. Considering the many uncertainties of the problem, the numerical model, which describes the wall failure surface in a simple way, should be an effective tool for investigating the response of masonry structures. So far, many analytical models describing the wall failure surface have been presented in the literature [16, 17].

One of the important mechanical characteristics for calculating and defining the response of masonry structures is creep. Difficulties in creep modeling are attributed to the stochastic nature of creep deformation and its dependence on a large number of interdependent parameters (e.g. types of masonry elements and binder, relative humidity and history and level of applied load) which makes the development of a single, general, yet accurate mathematical model nearly impossible [18]. Knowing the amount of creep and its modeling in masonry structures is necessary for efficient design of new structures and for realistic assessment and monitoring of the response of historical buildings. In the last 70 years, a significant number of empirical models have been developed to predict the creep of concrete and masonry using conventional mathematical methods.

3. DEVELOPMENT OF ANNs AND THEIR APPLICATION IN CONSTRUCTION

In recent years, artificial intelligence, as well as ANNs, have attracted considerable attention regarding their applications in a large number of scientific fields, which are based on solving problems and managing large amounts of data [5]. From the first days of the emergence of ANNs, they have made an exceptional contribution to the improvement of various scientific fields, so they have also found their application in construction engineering. [10]. ANNs represent a typical example of an interdisciplinary approach that solves various engineering problems that cannot be solved by traditional modeling and statistical methods.

ANNs are computer models inspired by the way the human brain works, where a large number of neurons work in parallel to process complex information. ANN works through the process of training (training) and testing. During the training process, the network goes through a data set where the input and corresponding output results are known. In the testing process, the network is tested on new data that was not used during training. When training is complete, the network operates in a trained state – a process where it receives new inputs and generates outputs based on learned connections and patterns. In this mode, the network can be used for data analysis and prediction in specific applications [9].

The need to process a large amount of data from certain databases in the construction industry, as well as adequately defining the dependence between output and input parameters, a certain number of interdependent variables, can be efficiently implemented using ANN. They simulates well the complicated, complex behavior in which the influences of different physical factors and characteristics are superimposed [9].

In the field of construction, many problems, especially in the field of building materials and engineering design, construction management, as well as programmatic decision-making, were influenced by many uncertainties that could be solved not only for the needs of mathematical, physical and mechanical calculations, but also largely depended on the experience of engineers [7].

The first paper dealing with the application of ANN in construction was published by Adeli and Yeh in 1989. Since then, the number of scientific papers published on the application of ANNs in construction is large, with most of these papers dealing with some kind of pattern recognition or learning problem [8]. ANNs have gained wide interest in civil engineering problems where they are mainly used as an alternative to statistical and optimization methods, as well as in combination with numerical simulation systems.

The main applications of artificial neural networks are the problems of identification and prediction, i.e. decision-making, pattern recognition, optimization, as well as data control and analysis. The application of ANNs in construction problems where numerical dependencies could not be defined until now is particularly noteworthy, namely geomechanics and materials science, where data for construction purposes were mostly obtained experimentally. Also, ANNs have found application in the organization of construction and monitoring the construction of buildings, i.e. in the tasks of predicting the performance of construction projects in different phases of projects and estimating construction costs, predicting the amount of materials for structures and production rates, safety at work, the construction process, dimensioning and damage detection of both concrete and steel structures, in the field of hydraulic engineering where their application is expressed in the arrangement of water courses, as well as civil engineering in the design of roads. Therefore, where construction tasks are already solved by classical numerical and statistical prediction methods, the use of artificial neural networks is possible and more competitive, without the need to reformulate or set the task in any other way.

4. APPLICATION OF ANNs IN DEFINING THE MECHANICAL CHARACTERISTICS OF MASONRY STRUCTURES

The design of masonry structures in the past was based mainly on the fundamental experience of the designers, who knew the laws of static structures as empirical knowledge, and not as an exact science, and as such they were mostly transmitted orally [19]. If we draw a parallel with ANN, we come to the conclusion that their application in construction will enable the transfer of knowledge, which this time is precisely defined.

Defining the mechanical characteristics of masonry structures is classified in materials science. With the rapid progress, development and application of artificial neural networks in construction, it can be said that they have found their application in materials science, although it is too early to claim that the method is fully established. Examinations of the mechanical characteristics of materials are carried out using experimental tests, both "in situ" and in the laboratory, whereby the obtained results are sometimes difficult to interpret, while the constitutive data are the results of the correlation of the applied materials. There is an obvious interest in applying ANN in the case where the model is built directly from some available experimental data. However, there are difficulties in the process of ANN formation because the development and processing of the available material is complex, and often lead to incomplete research and publication of the model.

By applying ANN in materials science, the unknown conventional analytical constitutive description can be directly replaced by an appropriately trained network. In this sense, ANN defines the law that governs the problem, still acting as a black box that behaves like the physical system it models [9].

Based on scientific knowledge that is available to the public, an analysis of the possibility of applying artificial neural networks in defining the mechanical characteristics of masonry walls was performed.

On the basis of the experimental tests of wall compressive strength known in the literature, J. Garzón-Roca et al. [20] formed a database of 96 laboratory tests, which they used to form an ANN for determining compressive strength. Using Matlab, a Multi-Layer Perceptron (MLP) network with forward flow was formed, which has two input parameters, the compressive strength of mortar (f_m) and the compressive strength of brick (f_b), while the output value is the compressive strength of the wall (f). In this study, six networks were defined where the number of neurons in the hidden layer was from 1 to 6, and then the ANN considered to give the best results was selected. The activation function of the hidden layer was a sigmoid function (SF) while the output layer contained a linear function (LF), where the network was trained using the Levenberg-Marquardt (LM) Back-Propagation (BP) algorithm. Of the total number of data from 96 studies, 80% was used for training the network and the remaining 20% was used for testing. For each of the six formed networks, the maximum, minimum, mean and standard deviation of the ratio of the compressive strength of the wall to the strengths from experimental research (f_{exp}) and the strengths obtained using the artificial neural network (f) were defined. Based on the analysis of the obtained results, it is concluded that the neural network with the 2–5–1 architecture achieved the best performance, with a standard deviation of less than 0.15. The results of ANN application for predicting the compressive strength of the wall were very satisfactory, and based on the model it is possible to obtain an empirical expression that allows the compressive strength of the wall to be calculated directly, without the need to program an ANN. A comparison of the results obtained using the ANN with four empirical expressions of other authors (Mann, Daiaratnam, Kaus-hik et al. and Dimiotis et al.), as well as with Eurocode 6 and ACI regulations, was also performed where it was observed that the different proposals do not fully agree with the experimental results, with an average deviation of about 20% from the actual value, which shows that the ANNs achieve good agreement with the experimental results.

To evaluate the compressive strength of walls made of hollow concrete blocks using ANN Q. Zhou et al. [21] considered two types of masonry elements and used 102 experimental data obtained in their own research but also based on results available in the literature. As the main parameters for defining the compressive strength of the wall (f), the ratio of height to thickness (h/t), the compressive strength of the masonry element (f_b), and the compressive strength of the mortar (f_m) were considered in accordance with the empirical models defined in the regulations for the design of masonry structures. 80 data were used to train the ANN, while 22 samples were used as the testing set, with the network with the 3–12–1 architecture achieving the best performance. In the study, a MLP ANN was used while the LM BP algorithm was used during network training instead of the commonly used BP method. SF was used in the hidden layer, and linear activation function was used in the output layer. To evaluate the performance of the ANN model, mean square error MSE, coefficient of determination (R2), mean absolute percentage error (MAPE) and integral absolute error (IAE) were monitored between predicted and experimental results. The predicted values are very close to the experimental results of both the training and testing sets in the developed network models. The obtained results were compared with the models defined in three regulations for the design of masonry structures (TMS 402, CSA S304.1 and Eurocode 6) and the model proposed by Sarhat et al, where it was observed that empirical methods underestimate the compressive strength by about 20% on average, while the predicted results from the model developed in this study closely agree with the experimental values, so the compressive strength of the wall can be calculated by applying the developed network assess very quickly.

The possibility of applying ANN to predict the compressive strength of the wall was also carried out by P. G. Asteris et al. [12] based on experimental data available in the literature by forming a database of 232 experimental data sets, which were obtained from 21 different experimental published works. As part of the research, they developed and implemented a number of different BP ANN models that were used to predict the compressive strength of the wall. During the ANN training process, out of 232 data, 66.81% was used to form the network, while 16.81% was used for validating the trained ANN, and 16.38% of the data was used for testing. During the selection of experimental data from the literature, the compressive strength of the masonry element (f_b), the compressive strength of the mortar (f_m), the ratio of the height and thickness of the masonry prism (h/t), the volume fraction of the masonry brick (VF_b) and the volume ratio of the mortar for the joints (VR_{mH}) were taken into account. The number of input parameters varied depending on the available number of experimental data. A number of different activation functions were used during ANN training, such as LS, Linear Transfer Function (purelin) - LF and Hyperbolic Tangent Sigmoid Transfer Function (tan-sig). The reliability and accuracy of the developed networks were evaluated using the Pearson correlation coefficient R and root mean square error (RMSE). In this model, the transfer functions are Hyperbolic Tangent Sigmoid Transfer Function (tansig) for the first hidden layer, LS for the second hidden layer and LF for the output layer. Out of the five models developed to predict the compressive strength based on the input parameters used, the one with three input parameters (compressive strength of the masonry element, compressive strength of the mortar, and wall-to-wall height-to-thickness ratio), the network with the 3–8–28-1 architecture achieved the best performance. The results of this network show that the proposed model predicts the compressive strength of the wall in a reliable and effective way.

In their paper, S. A. R. Shah et al. [22], based on their own experimental tests, defined some mechanical characteristics of walls that were formed from five different types of wall filling and four different mortars. For the purposes of this research, a ANN was formed that contained eight input neurons that defined characteristics such as: the amount of cement, sand, water, the ratio of cement to sand, the ratio of water to binder and the ratio of water to sand, as well as the type of connection in the wall, while the output layer contained two neurons, compressive strength and bending strength of the wall. The activation function of the hidden layer was a sigmoid function, while the algorithm was trained using the BP method. ANN model parameter estimates showed that for compressive strength prediction, the model was successful up to 75.5% in training data and 75.5% in validation data, while in case of flexural strength prediction, these values were even higher, 99% for training data and 97% for validation data.

S. Carozza and M. Cimmino in research [2] indicated that it is possible to form an ANN based on a small amount of data that is sufficient to obtain reliable results regarding the compressive strength of the wall. The study is not limited to specific wall systems, but is based on a heterogeneous sample, made of artificial or natural elements, with cement or non-cement mortar, and the results of 30 experimental tests were used in the research. For training the network, two sets of real data were used for testing: the first (19 samples) for the learning process using the back-propagation algorithm; the second (11 copies) for testing and checking the reliability of the network. In order to obtain the best possible results, several configurations of networks were tested in terms of the number of hidden layers and the number of neurons per layer, and it was observed that the network with the 5-3-5-1 architecture achieved the best performance. A sigmoid function was used in the two hidden layers as well as in the output layer, and the network was trained using the BP method. Despite the number of specimens of the learning set is not large (19 specimens), the formed ANN is effective for estimating the compressive strength of the wall. The results obtained using ANN lead to lower values than the values obtained based on empirical formulas.

O. Onat and B. Yön [14] conducted research that dealt with defining the compressive strength of the walls of old buildings of historical importance. The material characteristics and physical characteristics of 21 historical objects were used to predict the compressive strength of the wall, for which the volumetric weight, wall thickness, construction height, object dimensions and modulus of elasticity are known. An ANN model is used to predict the compressive strength of 13 different historical structures. One intermediate layer with seven neurons was used to construct the ANN, while the logistic function was used for prediction, and the back-propagation (BP) algorithm was used to minimize the procedure.

By filtering the data of a large database composed of 904 data from 23 different experimental tests for determining the compressive strength of masonry, K. S. Alotaibi, and K. Galal [1] extracted 326 tests divided into two groups, namely 124 tests where the masonry elements are hollow clay bricks and 202 tests of solid bricks. They used the data to form an ANN to estimate the compressive strength of a wall made of masonry units made of clay. The proposed ANN considered the important parameters that affect the compressive strength of the wall, including the strength and type of clay masonry unit, mortar type, and slenderness ratio. In this case, the input layer consists of three neurons, element compressive strength (f_b), slenderness (h/t) and coefficient C, while the output layer consists of one neuron defining the compressive strength of the wall (f) made of clay masonry elements. All ANNs have one hidden layer with the number of neurons ranging from 1 to 15. The proposed coefficient C is equal to the product of the coefficients (C_b) and (C_m) to account for the brick unit type and mortar type, respectively, C_b= 1 for solid brick and 0.5 for hollow brick, while the coefficient C_m= 1 for N type mortar and 2.34 and 3.23 for S or M type mortar, respectively.

Each of the 15 ANNs was trained on the data set, and three statistical indicators were defined for comparing the performance of the models. The indicators are the average ratio between the values obtained experimentally and the values predicted by the application of the ANN, coefficients of determination (R2) and coefficient of variation (C.O.V.). Based on the training results, the best performance is given by the neural network model with 3–10–1 architecture, while BP was applied for its training. The proposed model showed a good ability to predict the compressive strength of a wall made of clay masonry elements.

Research by S. R. Muthukumar and Jegatheeswaran [15] deals with the prediction of the compressive strength of a wall made of autoclaved aerated concrete elements using ANN. 36 data sets were collected for testing, whose characteristics were checked and compared with other empirical calculation methods that served for validation. To supplement the data sets, 90 test data sets containing test results for more than 300 prototypes were collected and published in the literature. As essential criteria for defining the compressive strength of a wall based on empirical models, the ratio of height and thickness (h/t) of a masonry element, its compressive strength (f_b) and the compressive strength of mortar (f_m) were considered. The results obtained by applying the ANN with the 3–1–12–1 architecture achieved the best performance, between the layers a simple LF was used, while the BP algorithm was used in the training process. The results were compared with the three proposed empirical expressions, concluding that the predicted values are very close to the experimental data, and that the empirical approaches underestimate the compressive strength of the wall by 18% on average.

As walls are by nature anisotropic and brittle materials, the realization of reliable experimental tests under biaxial stress conditions is very complicated. How artificial intelligence can be used to approximate experimentally obtained results P. G. Asteris and V. Plevris [23] form ANNs that generate failure curves of biaxially stressed walls. In their study, they use experimental data containing 102 wall samples. Feed-forward (FF) BP Neural Network (BPNN) with two hidden layers, one input layer and one output layer is applied. The input layer has one neuron corresponding to the angle θ, for the first two cases (θ =0° and θ =22.5°) the networks have two hidden layers with 8 nodes each, while in the third case (θ =45°) two hidden layers have 12 nodes each. The transfer function used is the hyperbolic tangent function (HTF), the same for all hidden and input layers, while the transfer function for the output layer is LF. Three ANNs are trained with input and output data, and then the neural network is asked to produce the entire refraction curve for each angle as its output, also filling in the gaps between experimental points with appropriate approximations, for a set of 64 points. After training the network, it is observed that the obtained results are of satisfactory accuracy, while the approximation between the training data points seems to be adequate. The results show the great potential of using ANN for approximating wall failure under biaxial loading, and further research is needed regarding the use of ANN to generate the failure surface for any angle θ. In the following research [16], the same authors form an ANN that generates a 3D failure surface under biaxial stress for walls at any angle of application of the load. First, for each angle θ (0°, 22.5°, 45°) an ANN was trained with experimental data as inputs (three neural networks in total) and a 2D failure curve was obtained. Next, a global ANN was trained based on the results of the previous three ANNs using the angle as input, and then asked to fill in the gaps between the angles θ as well, providing the entire 3D failure surface for any failure angle. As the results of the previous three formed ANNs were used as training patterns for the global network, it means that it was formed based on 101*3 = 303 training patterns, since 101 points were used for each angle (0°, 22.5° and 45°). The global ANN is also a BP network and consists of 9 nodes per hidden layer (2-9-9-1). The two inputs are the angles φ (0 90) and θ (0 45), while the output is the radius of the failure surface r. The transfer function of the global ANN is HTF, which was also used in the first three networks, while the transfer function for the output layer is LF. The obtained data indicate that the global ANN manages to provide valuable information, provides a smooth 3D surface, and the agreement with the experimental data is excellent.

After the previous research [16], P. G. Asteris and V. Plevris [17] propose the use of ANN for modeling the anisotropic behavior of the wall in the biaxial stress state and the formation of the fracture surface of the masonry material in a dimensionless form for any quadrant of the stress state. Five ANNs were trained, one for each angle θ (0°, 22.5°, 45°, 67.5° and 90°), BP networks with one hidden layer, one input layer and one output layer were used. The input layer had one neuron corresponding to an angle (in the range [0, 2π]), which defines the relationship of the principal stresses, while the output layer had one node corresponding to the distance (radius) of a point on the failure curve to the origin of the axis. The hidden layer of all networks had 4 nodes. After training the network with input and output data, each network was asked to produce solid curves for each angle. The transfer function is HTF, the same for all hidden and input layers, while the transfer function for the output layer is LF. This scheme was used in all five networks that managed to fit all data during training with very good accuracy, providing smooth curves in all cases. The final purpose of the study was to create a model that will be able to predict the entire refraction curve not only for predefined angles, but for any angle θ, from 0 to 90. After the five artificial networks were trained and produced their results, a global network was formed that used the results of the previously formed networks as inputs with the angle, with one additional input. The ANN thus formed was asked to fill in the gaps between the corners as well, providing the entire 3D failure shape for any angle θ and any principal stress ratio, for all four quadrants. The global network is a BP network with one hidden layer containing 10 nodes. The two inputs are angles (0 to 4 π – two full circles) and θ (0° to 90°), while the output is the distance (radius) r. The transfer function of the global network is the HTF, which was also used in the first five networks. The proposed network has proven to be reliable and provides valuable results. The failure surface corresponds with high precision to the experimental data, and on the other hand, it is given in a dimensionless form, so it can be applied to other masonry materials of similar geometry and properties. The derived surface provides valuable information on hitherto unexplored areas of wall failure which gives insight into the overall mechanics of wall failure.

In the paper conducted by M. M. R. Taha et al. [18] only experimental results for one type of masonry element were used to form a FF network. Test results from 14 test groups were included in the training of the network, and a standard N-type mortar was used. Given the data available for creep modeling, only four parameters were considered: stress level (s), relative humidity (RH), load application time (t_0), and creep measurement time (t). The ratio of surface area to volume is not taken into account because it is the same for all prisms with the same humidity. ANN for creep prediction consists of an input layer, a six-neuron hidden layer, and an output layer. The network uses a LS transfer function and a linear output function, while the BP algorithm was used during network training. The comparison of the compliance of the creep obtained by the application of ANN in relation to the experimentally obtained data of the measured creep is within ±15%. The RMSE between the predicted creep coefficient and the measured creep coefficient for the different tested groups did not exceed 0.11, which reflects the correct prediction. Despite the relatively limited amount of data used to develop the network, the ANN model was more accurate than conventional models in predicting creep.

M. M. R. Taha et al. [24] use data concerning the creep of masonry structures as datasets for training and testing artificial neural networks. As all experiments were performed on specimens of the same size, only four parameters were considered for creep modeling: stress level, relative humidity, load application time, and creep measurement time, and the effect of temperature on creep was not investigated. A total of fifteen ANNs were formed to predict the amount of creep, and in all networks the input layer contained four neurons. Out of the total number of networks, the first group consisted of seven with one hidden layer in which the number of neurons ranged from one to ten, and in all seven networks the LS was cut. The second group consisted of eight networks that had two hidden layers, with the number of hidden neurons ranging from two to six, and the efficiency of purely linear transfer functions and LS transfer functions was tested. All 15 networks use a BP training algorithm as the learning rule for the network with an update criterion of Levenberg-Marquardt weights. A learning matrix including 47 training samples drawn from ten training groups was used to train the networks. The structure of the network as well as its transfer functions clearly influence the number of iterations required during the network training procedure to achieve the target mean square error (MSEE), where only the 4-3-3-1 network with LS applied in both hidden layers did not reach the target value. Depending on the complexity of the network and applied transfer functions, the number of required iterations ranged from 70 for a network with a 4-6-1 structure with LS, to 650 iterations for a 4-6-4-1 network with both transfer functions being LS. Each of the 15 networks was tested using a matrix of 80 samples drawn from four test groups. Using regression analysis, it was found that eight out of 15 networks are able to predict creep with a deviation of 15%, while the other seven networks are not able to achieve this accuracy, but the relative accuracy ranges from 30 to 50%. Comparisons between predicted and measured creep were performed by estimating the prediction error (PE) which measures the root mean square error between the predicted creep obtained from the model and the measured creep. Based on the prediction error for 15 networks and the modified Burgers model, it is obvious that the creep prediction models using ANN have a lower prediction error and therefore higher accuracy than the classical creep prediction model using conventional regression analysis.

M. M. Abed et al. [25] use the experimental results of the wall creep test program conducted at the University of Calgary over the past 15 years to form ANNs. The creep deformation of masonry prisms made of only one type of masonry elements, exposed to different stress levels and environmental conditions, was monitored. This study introduces creep prediction by developing a Focused Time-Delay Neural Network (FTDNN) based model that could detect and consider the time dependence that is the main factor in creep deformation in masonry walls. The grid has a 4-2-1 structure. The network between the input layer and layers uses, LS and tan-sigmoid transfer function and LF. In the ANN training phase, the goal was to achieve a root mean square error of 0.0001, with the time-delay neural network (FTDNN) model successfully achieving the target value after 48 iterations. Statistical analysis of the results obtained using the neural network model with a time delay showed that it has a relatively small prediction error, less than 15%, compared to the RNN model and the Burger model.

The aim of the study conducted by A. El-Shafie et al. [26] is to investigate the use of a simpler ANN that uses radial basis functions in its only hidden layer. For creep prediction, a model based on radial basis function neural networks (RBFNN) is proposed, and the obtained results are compared with the results of a MLP neural network, whose model was developed for the same purpose. In this study, the MLPNN contains four neurons in the input layer, corresponding to current time (t), load application time (t_0), and long-term voltages and relative humidity are considered. The output layer has only one neuron corresponding to the predicted time-dependent creep. The error between the measured and predicted creep is fed to a learning criterion that adjusts the network parameters in such a way as to minimize the root mean square error. Although they have a complex architecture, the MLPNN models could not provide creep with a prediction error of less than 15% in all cases. The developed MLPNN model can then be used to predict creep corresponding to any other combined set of input variables. In this study, the analysis of more complex MLPNN architectures than those reported by R. Taha et al. [24] is done to investigate the possibility of improving or worsening the accuracy of predicting time-dependent creep in masonry structures.

5. ANALYSIS OF THE PRESENTED WORKS

Within this paper, the works using ANN, in the field of defining the mechanical characteristics of masonry structures, were analyzed. A total of fifteen papers published in the period from 2003 to 2024 were analyzed. ANNs found their application in the process of defining the mechanical characteristics of masonry structures, namely compressive strength, bending strength, consideration of failure under biaxial loading, and creep of masonry walls (Table 1).

Table 1: Distribution of analyzed papers in relation to areas of application

Mechanical characteristics	Papers
Compressive strength	[1], [2], [12], [14], [15], [20], [21], [22]
Bending strength	[22]
Failure under biaxial loading	[16], [17], [23]
Creep	[18], [24], [25], [26]

The classification of neural networks into groups of small, medium, and complex is introduced solely for the scope of this study and is not based on a standardized or generally accepted categorization in the field. The proposed division enables a more systematic comparison of the analyzed papers based on the complexity of the applied neural network models. The analysis can be done based on the complexity of the neural networks used in solving certain problems (Table 2). The group of simple ANNs includes networks that use only a few layers, usually 2, with a smaller number of input parameters and simple architectures. A network with 3 layers is included in the group of medium complexity, where the number of input parameters and the complexity of the architecture grow, but it is still not too demanding in terms of calculation. The complex group consists of networks with additional parameters and more complex architectures, these networks use 3 layers, but with a larger number of input parameters, with the application of advanced training algorithms and activation functions, which makes them more demanding for implementation and training.

Table 2: ANN complexity depending on ANN structure

Complexity	Simple	Medium	Complex
Paper	[1], [15], [18], [20]	[14], [16], [17], [21], [22], [26]	[2], [12], [23], [24], [25]

By analyzing the complexity of the applied ANN model, the least complex problems that define compressive and bending strength are singled out, when simple MLP and BPNN networks are used, with one hidden layer. A MLP is used in all cases except for biaxial stress, where BPNN is dominant. Defining the failure of a wall exposed to biaxial loading is among moderately complex problems when BPNN networks with back-propagation with slightly more neurons in the hidden layer are mainly used, which shows that the problem is somewhat more complex. BPNN is used for biaxial stress, probably due to its ability to process more complex data structures. When it comes to defining wall creep as the most complex topic, several different networks are used such as MLPNN, FTDNN, RBFNN, which indicates the need for different modeling approaches and a greater need for models with dynamic time and more complex transfer functions. The conclusion is that the more complex the physical process and the more dependent on time dynamics such as crawling, the more complex the neural network is used. Based on the conducted analysis, it can be seen that the most commonly used type of neural network when solving almost all problems is MLP (BPNN), while RBFNN is used only in one paper for creep prediction [26], and FTDNN (time delay network) is used in a paper for creep prediction [25].

All analyzed papers considered in this study applied the same type of artificial neural network, specifically the Multilayer Perceptron (MLP) trained using the Backpropagation algorithm (BP ANN). This type of network represents the most commonly used ANN architecture for regression and classification tasks in the field of civil engineering, particularly for predicting the mechanical properties of masonry structures. The consistent application of the same ANN type across all reviewed studies enables a systematic comparison of results and facilitates the identification of potential advantages and limitations of this approach in modeling the mechanical behavior of masonry walls.

When analyzing the connections between the problem being processed and the activation functions in the hidden and output layers, it is observed that LF is in the output layer, except for bending strength and a few cases where it is not explicitly stated in the paper. This approach is fully justified because continuous values of physical characteristics (eg pressure, deformation, stress) are predicted. It is observed that sigmoid and LS are used in simpler problems (compressive and flexural strength), while HTF (tansig) is used for biaxial stress and creep, indicating the need to model both positive and negative values. It is observed that when defining compressive strength, the sigmoid function dominates, which may indicate the need to stabilize the output in a limited range, with biaxial stress and wall failure, tansig is more often used, which may mean that the data are balanced around zero, while for creep, a combination of LS and tansig functions is used, which may be due to time dependence and the need for nonlinear modeling. It is concluded that when static material parameters are defined (compressive strength, bending strength), sigmoid functions are dominantly used in the hidden layer, in the case of a more complex stress state (biaxial stress, creep), HTF is more often used, whereby the LF in the output is universal, which makes sense because physical quantities in a continuous range are predicted.

It is also possible to perform ANN analysis depending on the applied training algorithm and the type of problem being solved. Backpropagation is dominant for simpler problems (compressive and flexural strength), while Levenberg-Marquardt is used for biaxial stress, which may mean that this algorithm better solves problems with complex stress states. Creep, as a complex problem, uses a combination of LMBP (Levenberg-Marquardt Backpropagation) and Gradient Descent, which indicates the need for more sophisticated optimization

During the analysis of the proposed ANN models, a mutual relationship between the type of data, the number of samples used for training the network and the complexity of the network is observed. In most cases, experimentally obtained results were applied (compression strength, creep,) or based on them, numerical values were obtained that were used for further training of ANN (wall failure under biaxial stress), whereby historical data appears in only one case [14].

Experimentally obtained data from laboratory testing have a small number of samples (≤100) and are used for simple physical properties of materials, such as compressive strength and flexural strength, where these problems usually have linear or slightly non-linear characteristics that can be modeled with a small number of data. For a small number of samples, simpler networks with fewer layers and neurons were used. Typical networks used with small number of samples are MLPNN (Multilayer Perceptron Network), Feedforward Neural Networks and Sigmoid Activation Functions because they work well with smaller datasets. Smaller datasets use shallower networks with fewer neurons to reduce the likelihood of overfitting, while larger and more complex networks require more data to avoid overfitting.

A medium number of samples (100–300) are usually combinations of experimental and numerical data collected from the available literature. A combination of different types of samples (eg different types of masonry elements or materials) can also be used when problems with a larger number of variables and pronounced nonlinearities occur. The average number of samples follows networks with additional neurons in hidden layers, deeper structures, and more neurons per layer. These networks have a better ability to generalize, but are still not too complex for overlearning to occur. In this case, Backpropagation neural networks were applied, while tansig and LS were used as activation functions to improve the modeling of nonlinear phenomena. Medium-sized data sets allow the use of deeper networks with more neurons and a better ability to capture non-linear patterns.

A large number of samples (≥300) in this case were obtained based on the results of simpler ANNs, and are used to describe complex interactions in materials, i.e. defining the anisotropic behavior of the wall in the biaxial stress state and the formation of the fracture surface of the masonry material in a dimensionless form. Deep multi-layer networks and specialized architectures such as RBFNN (Radial Basis Function Neural Network) used when the data is diverse and complex, FTDNN (Functional Time-Delayed Neural Network) is used to analyze weather phenomena (material creep). Typical activation functions used are a combination of LS and tansig functions to model complex phenomena. It is observed that as the number of samples increases, neural networks become more complex - moving from simple MLP models to deeper BPNN and specialized architectures like FTDNN and RBFNN.

5.1. Practical application of the presented results and future trends

Based on the data analysis, it can be seen that this kind of application of ANN can be widely used in engineering and industrial practice, especially in the field of defining the mechanical characteristics of walls, as well as in materials science. These data help in defining the mechanical characteristics of masonry structures, and their advantages are:

- ANN, based on previously collected data, enables fast and reliable prediction of mechanical characteristics without the need for physical testing of walls made of masonry elements and mortar with different mechanical properties;
- Formed ANN models can be used to generate empirical expressions that allow fast calculations without retraining the network;
- Faster testing, cost reduction and laboratory testing through neural networks that predict results based on previous experiments;
- As experimental wall tests are expensive and time-consuming, ANN enables a smaller number of physical tests with the same or better results;

- Replacement of classic test methods (eg destructive tests) with software predictions;
- Faster design of new materials because it enables the simulation of different material compositions before experimental validation;
- Modeling time-dependent changes in materials such as the creep of masonry walls;
- Prediction of the long-term behavior of structures without the need for multi-year experiments;
- Prediction of material failure before the formation of a masonry wall failure mechanism;
- Planning preventive maintenance based on simulations, which avoids the formation of a failure mechanism;
- Speeding up the testing process – Models can quickly analyze data and make decisions without the need for time-consuming experiments;
- Reduction of human errors – Automated processes increase measurement accuracy;
- No work uses Convolutional Neural Networks (CNN) or Recurrent Neural Networks (RNN), which may be a potential area for further development;
- Hybrid models that combine different types of neural networks can improve prediction accuracy.

This approach has its drawbacks as well as limitations:

- If the dataset is too small, the network may give inaccurate predictions and be unreliable in real-world conditions;
- Large data sets are necessary for accurate models, and these are not always available;
- Accurate training of the network with quality data is required to avoid wrong conclusions;
- Insufficient data variety may cause the model to fail to recognize certain material types or conditions;
- Limited accuracy of neural networks in long-term predictions, as small perturbations can cause large errors over time;
- Neural networks can give false positive or false negative results, which can be dangerous in critical applications.

By analyzing the presented models, it was observed that increasing the number of hidden layers or the number of neurons in each layer does not necessarily lead to a more accurate prediction of mechanical characteristics, while the use of a non-linear calculation (mainly based on log sigmoid transfer functions) instead of a linear one may not provide better performance of the final results. It was also observed that in some cases, increasing the complexity of the ANN architecture does not mean defining a better result. As in the studies presented so far, one type of ANN, namely BP, was mainly used, it is necessary to apply other types of artificial neural networks in the following studies.

Despite the undeniable possibilities of applying artificial neural networks, model improvements are still needed in order to be considered a reliable tool for defining the mechanical characteristics of masonry walls. The network's ability to predict mechanical characteristics is limited to the input parameters, so it is necessary to include other input parameters that can affect the mechanical characteristics of the walls in some subsequent tests. As the networks are formed only for certain types of walls as well as applied bonding materials, it is necessary at some point to form an artificial neural network that could define the mechanical characteristics of walls that are formed from different types of masonry elements, their classes, groups to which they belong as well as the appropriate bonding material. However, since the research carried out so far did not include all the mechanical characteristics of masonry walls, it is necessary to consider other useful output parameters in further research into the application of artificial neural networks, such as shear strength, Young's modulus of elasticity and others.

6. CONCLUSIONS

In recent decades, a rapid development and penetration of digital technologies in the field of construction has been observed. With the appearance of artificial neural networks, their application was observed in almost all areas of construction engineering, even in the definition of some mechanical characteristics of masonry structures, for which numerical dependencies have not been determined. Based on the review of scientific research available so far in the literature related to defining the mechanical characteristics of walls, it can be seen that in recent years ANNs have found their application in solving this complex construction problem, which is of great importance for the process of designing masonry structures. This paper presents an analysis of scientific researches that dealt with the definition of some mechanical characteristics of masonry structures, using artificial neural networks. It was observed that neural networks were successfully used as prognostic models for defining only certain mechanical characteristics of walls, compressive strength, wall failure and creep, while other mechanical characteristics were not treated. All artificial neural networks were formed for those cases in which there are already some previous experimental researches, while the verification of the obtained results was mainly performed on the basis of already known numerical dependencies.

ANNs have shown an exceptional ability to predict the mechanical characteristics of masonry structures, with greater accuracy than classical empirical models. The main advantage of using artificial neural networks in defining the mechanical characteristics of masonry walls is reflected in the ability to continuously increase the accuracy of the model as experimental data becomes available for further testing. Also, the proposed artificial neural networks can be expanded in order to obtain better results and their further improvement. By forming artificial neural networks and their models, many scientific and engineering problems that require knowledge of the mechanical characteristics of masonry walls will require less time and expensive testing. In addition to the presented review and analysis of the application of artificial neural networks in defining the mechanical characteristics of masonry walls, this paper also provides directions for some further research. The analysis shown in this way can be valuable both for future researchers and for practitioners who try to implement artificial neural networks in the process of defining the mechanical characteristics of walls.

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