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APPLICATION OF ARTIFICIAL NEURAL NETWORKS IN CIVIL ENGINEERING

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Original scientific paper

The application of artificial neural networks for solving complex civil engineering problems is of huge importance for the construction design process. They can be successfully used for prognostic modelling in different engineering fields, especially in those cases where some prior (numerical or experimental) analyses were already made. This paper presents some of the positive aspects of neural network's model that was used for determination of fire resistance of construction elements.

Keywords: *artificial neural networks, civil engineering, fire resistance, prognostic modelling*

Primjena umjetnih neuronskih mreža u građevinarstvu

Izvorni znanstveni članak

Primjena umjetnih neuronskih mreža za rješavanje složenih građevinskih problema je od ogromne važnosti za proces projektiranja. One se mogu uspješno koristiti za prognostičko modeliranje u različitim inženjerskim područjima, osobito u onim slučajevima u kojima već postoje neka prethodna istraživanja (numerička ili pokusna). Ovaj rad prikazuje neke od pozitivnih aspekata modela neuronske mreže kad se koriste za utvrđivanje požarne otpornosti građevinskih elemenata.

Ključne riječi: *građevinarstvo, prognozni model, požarna otpornost, umjetne neuronske mreže*

1 Introduction

Artificial neural networks are typical example of a modern interdisciplinary subject that helps solving various different engineering problems which could not be solved by the traditional modelling and statistical methods [3, 4, 6]. Neural networks are capable of collecting, memorizing, analysing and processing large number of data gained from some experiments or numerical analyses. They are an illustration of sophisticated modelling technique that can be used for solving many complex problems. The trained neural network serves as an analytical tool for qualified prognoses of the results, for any input data which were not included in the learning process of the network. Their operation is reasonably simple and easy, yet correct and precise.

Using the concept of the artificial neural networks and the results of the performed numerical analyses as input parameters, the prediction model for defining the fire resistance of RC columns incorporated in walls and exposed to standard fire from one side, has been made.

A short description of the numerical analyses of columns exposed to standard fire ISO 834, conducted by the computer software FIRE is presented in this paper. The software is capable of predicting the nonlinear response of reinforced concrete elements and plane frame structures subjected to fire loading, carrying out the nonlinear transient heat flow analysis and nonlinear stress-strain response associated with fire.

Besides the numerical analyses, the goal of the research presented in this paper was to build a prognostic model which could generate outputs for the fire resistance of reinforced concrete columns incorporated in walls, for any given input data, by using the results from the conducted numerical analyses, as input data. The trained neural network served as an analytical tool for qualified prognoses of the output results, such as the time of fire resistance of reinforced concrete columns, for any input data which were not included in the learning process of the network.

2 Artificial neural networks – basic concepts

The artificial neural networks (further referred as neural networks), together with the fuzzy logic and genetic algorithms, belong to the group of symbolic methods of intelligent calculations and data processing that operate according to the principles of soft computing. Neural networks are developed as a result of the positive features of a few different research directions: data processing, neuro-biology and physics. They are a typical example of one modern interdisciplinary field which gives the basic knowledge principles that are used for solving many different and complex engineering problems that could not be solved otherwise (using the traditional modelling and statistical methods)[3, 4, 6].

The inspiration for foundation, development and application of artificial neural networks came out of the attempt of understanding the work of human brain and from the aspiration of creating an artificial "intelligent" system for data calculation and processing that are typical for human brain. Mainly because of that the artificial neural networks are very similar to the biological neural networks. Both networks have similar structure, function, and technique of data processing and methodology of calculation. Artificial neural networks are presented as a simplified mathematical model, a model that is similar and analogous to the biological neural networks. They can easily simulate the basic characteristics of the biological nerve system. The networks are capable of gathering, memorizing and processing numerous experimental data. Some of their basic characteristics are the following: they can analyse large number of data, they can learn from the past data and they can solve problems that are complex, not clear and problems that do not have only one solution. Because of that, the artificial neural networks are often a better calculation and prediction method compared to the classic and traditional calculation methods [3, 4, 6].

Researches made around the world showed that neural networks have an excellent success in prediction of data series and that is why they can be used for creating prognostic models that could solve different problems and tasks [3, 4, 5, 6].

2.1 Neuron

Processes inside the biological neural networks are very complex and they still cannot be completely studied and explained. There are hundreds of different types of biological neurons in human brain, so it is almost impossible to create a mathematical model that will be absolutely the same as the biological neural network. However, for practical application of artificial neural networks, it is not necessary to use complex neuron models. Therefore, the developed models for artificial neurons only remind us to the structure of the biological ones and they have no pretension to copy their real condition [3, 4, 5, 6].

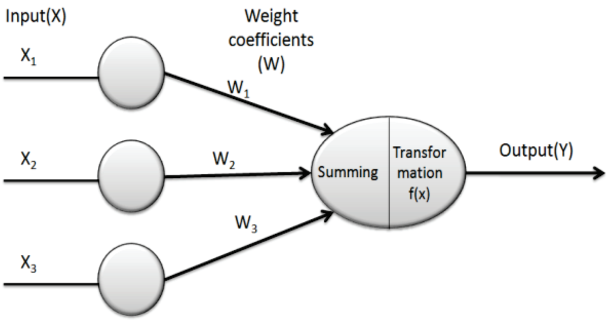

Figure 1 Model of artificial neuron

The artificial neuron receives the input signals and generates the output signals. Every data from the surrounding or an output from other neurons can be used as an input signal. The model for an artificial neuron is shown in Fig. 1.

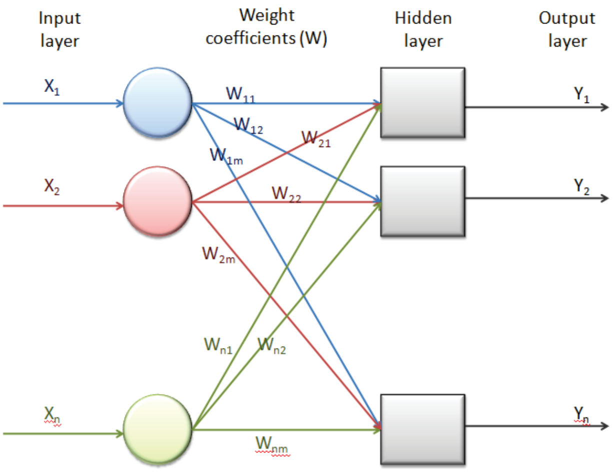

Figure 2 Model of one layered artificial neural network

2.3 Neural network

Neural network is composed of numerous mutually connected neurons grouped in layers. The complicity of the network is determinate by the number of layers. Beside the input (first) and the output (last) layer, network can have one or few hidden layers (Fig. 2). The purpose of the input layer is to accept data from the surroundings. Those data are processed in the hidden layers and sent into the output layer. The final results from the network are the outputs of the neurons from the last network layer and that is actually the solution for the analysed problem.

The input data can have any form or type. The basic rule is that for each data we must have only one input value. Depending on the problem's type, the network can have one or few outputs.

2.2 Weight coefficients

Weight coefficients are the key elements of every neural network. They express the relative importance of each neuron's input and determine the input's capability for stimulation of the neurons [3, 4, 5, 6].

Every input neuron has its own weight coefficient. By multiplying those weight coefficients with the input signals and by summing that, we calculate the input signal from each neuron. In Fig. 1 the input data are marked as X_1, X_2 and X_3, and the appropriate weight coefficients are W_1, W_2 and W_3. The input neuron impulses are W_1X_1, W_2X_2 and W_3X_3. Neuron registers the summed input impulse which is equal to the sum of all input impulses: $X = W_1X_1 + W_2X_2 + W_3X_3$. The received impulse is processed through an appropriate transformation function (activation function), $f(x)$, and the output signal from the neuron will be: $Y = f(x) = f(W_1X_1 + W_2X_2 + W_3X_3)$.

Weight coefficients are elements of the matrix W that has n rows and m columns. For example, the weight coefficient W_{nm} is actually the m^{th} output of the n^{th} neuron (Fig. 2). The connection between the signal's source and neurons is determined by the weight coefficients. Positive weight coefficient means speeding synapse and negative coefficient means inhibiting synapse. If $W_{ij} = 0$ it means that there is no connection between these two neurons.

One very important characteristic of neural networks is their ability for weight adjustment according to the received history data, which is actually the learning process of the network [3, 4, 6].

2.4 Activation function

The main purpose of the activation (transformation) function is to determine whether the result from the summary impulse $X = W_1X_1 + W_2X_2 + ... + W_nX_m$ can generate an output. This function is associated with the neurons from the hidden layers and it is mostly some non-linear function. Almost every non-linear function can be used as an activation function, but a common practice is to use the sigmoid function (hyperbolic tangent and logistic) with the following form: $Y_t = 1/(1 + e\hat{}(-Y))$, where: Y_t is normalized value of the result of the summary function. The normalization means that the output's value, after the transformation, will be in reasonable limits, between 0 and 1 [3, 4, 5, 6].

If there is no activation function and no transformation, the output value might be too large, especially for complex networks that have few hidden layers.

2.5 Architecture of neural networks

A very important aspect of neural networks is how to connect the network elements. There are many different models of neural networks and many different ways for their classification [3, 4, 5, 6]. Generally speaking, types of networks are divided according to: number of layers (one layered and multi layered networks), connection type between neurons (layered, fully connected and cellular), learning process (feed forward and feedback), data type (binary and continuous networks), course of information spreading (supervised, partly supervised and unsupervised networks), etc.

2.6 Network's training process

The artificial neural networks have several basic characteristics, among which their learning capability takes an important place (this capability brings them closer to the real world and human thinking), together with their capability of discovering connection between chaotic and incomprehensible data and their generalizing capability (the network will give quality outputs even though the input data are not completed). In many cases it is shown that the neural networks are a better calculation method compared to the classic methods, mostly because of their capability to analyse data that contain errors, or to solve problems that have no reasonable solution and to learn from the past data. The training (learning) process of neural networks consists of periodic data transmission through the network and compartment of the received input values with the expected ones. If there is a difference between those values, then a weight coefficient's adjustment (modification of the neuron connections) has to be made. This process is repeated a few times until the network reacts the way we want it to react, or until all the weight coefficients from all the training data are being adjusted. When the network gives correct outputs for all of the training data, we can say that it is a trained network. After the training process the network should be able to generate outputs for new input data different from the training ones [3, 4, 5, 6].

The learning and training process that occurs inside neural networks is of huge importance for their applicability in solving engineering problems.

3 Application of neural networks for prognostic modelling of the time of fire resistance of reinforced-concrete columns

3.1 General

The legally prescribed time period during which a structure must stay stable and safe under fire, is actually the time in minutes which represents the fire resistance of a structure. The length of this time period is legally binding in almost every country and it depends on: the height, number of flats, floor area, capacity, content and purpose of the structure, the distance of fire stations and fire brigades, as well as on the fire protection system of the structure [1].

The fire resistance of a structure can be determined based on the estimated fire resistance of whole structure or of each construction element (columns, beams, slabs, walls, etc.). The fire resistance of a structural element is the time period (in minutes) from the beginning of the fire until the moment when the element reaches its ultimate capacity (ultimate strength, stability and deformability) or until the element loses its separation function [1].

Nowadays, as a result of many years of investigations, there are three basic methods for determination of the fire resistance of structural elements and their assemblies. The oldest method is the performance of a fire test of loaded elements, in compliance with the national regulations and standards, or comparison of the elements with the results from already performed tests on similar or identical elements. The second method implies the use of empirical formulae that are based on the results from performed fire tests and holds for a certain combination of: structure, material and protective coating. The third method represents an analytically elaborated approach to design elements with a predefined fire resistance and it is based on the principles of structural mechanics and theory of heat transfer [1].

For the last twenty years, particular importance has been given to analytical definition of the problem, but the need for getting answers to many questions in this field implies the application of new, modern and faster methods for determining the fire resistance of structures. The application of neural networks as such a method for building a prognostic model which can be used for predicting the fire resistance for structures and/or their elements is of a huge importance for the design process in construction [5, 6, 9, 10]. The modelling through neural networks can help, especially in those cases when some prior analyses were already made.

The goal of the research presented in this paper was to build a prognostic model which could generate outputs for the fire resistance of eccentrically loaded reinforced concrete columns for any given input data, by using the numerical results from the existing research program, as input data.

3.2 Prognostic model for eccentrically loaded columns

The columns as structural elements have an important role in preventing loss of global stability of structures under fire. If these elements do not suffer failure, damages shall be of a local character. Eccentrically loaded columns, treated in this paper, in most cases are external columns of the frame structures and are incorporated in a wall for separating the fire compartment and for that reason they are exposed to fire only from one side. The temperature fields in the cross section of this type of columns are non-symmetrical and in combination with the external loadings (axial force and bending moment) result with less fire resistance than in case when the columns are centrically loaded and exposed to fire from all four sides [1, 9, 10].

Numerical analyses concerning the behaviour of the eccentrically loaded reinforced concrete columns exposed to standard fire test only from one side are one part of the scientific research work [1]. As a result of her research work the computer program FIRE (FIreREsponse) was developed. This program is capable of predicting the nonlinear response of reinforced concrete elements and plane frame structures subjected to fire loading. The program carries out the nonlinear transient heat flow analysis (modulus FIRE-T) and nonlinear stress-strain response associated with fire (modulus FIRE-S). The solution technique used in FIRE is a finite element method coupled with time step integration [1].

Using the program FIRE the behaviour of eccentrically loaded columns exposed to standard fire ISO 834 was analysed and the influence of element geometry, concrete cover thickness, steel ratio and intensity of the axial force and the bending moment as dominant factors that influence the fire resistance of this type of columns was defined. The support conditions and column length were not varied. The columns were fixed at the bottom side and freely supported at the top side that allowed free expansion in longitudinal direction. The model of the RC columns that were concerned in the analyses is presented in Fig. 3 [1].

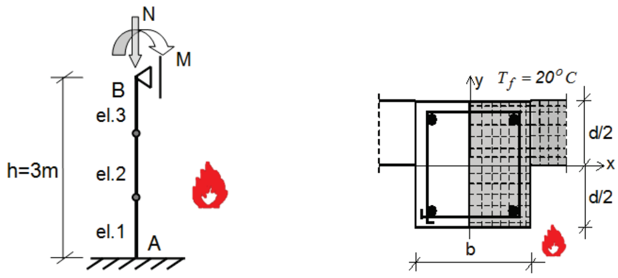

Figure 3 Eccentrically loaded RC column as a part of a wall that separates the fire compartment: geometry and support conditions, cross section geometry

The goal of the investigation presented in this paper was to build a prognostic model which could generate outputs for the fire resistance of eccentrically loaded reinforced concrete columns as part of a wall that separates the fire compartment, by using the numerical results as input data.

The neural networks prognostic model was developed by using the software Neural Tools ver.6. The numerical results given in [1] were used as input data and all data were grouped into two separate tables: the data for training and testing the neural network and data for predicting the value of the output variable. During that training process a total of 398 cases were analysed, of which 318 (80 %) belong to the group of cases for training and the rest (80 cases) were used to test the network. The following six independent variables were treated as input: dimensions of the cross section of the column (b and d), the concrete cover thickness (a), percentage of reinforcement (μ), load coefficient for axial force (η) and load coefficient for the bending moment (β). The output was only one variable: the fire resistance of the column expressed in minutes (t).

The load coefficient for axial force (η) and load coefficient for the bending moment (β) were defined from the M_b-N diagrams of the columns at ambient temperature [1]:

$$\eta = \frac{N}{N_{u,\max}}, \ \beta = \frac{M_\mathrm{b}}{M_{\mathrm{b}u}}, \tag{3}$$

where: N is axial force before action of fire, $N_{u,\max}$ is ultimate axial force when the bending moment is zero (defined from M_b-N diagram), M_b is bending moment before action of fire, M_u is ultimate bending moment corresponding to the ultimate axial force N_u [3].

$$N = N_g \gamma_{ug} + N_p \gamma_{up} = N \gamma_u \, . \tag{2}$$

Training and testing of neural networks is an iterative process that repeats the procedure of training and testing of several neural networks with different structure until it generates neural network which provides the best outcomes [2 ÷ 8]. For the multilayered networks with spreading the information forward (in one direction, from input to output layer) the learning cycle means determination of weight coefficients for the connections between neurons, where training is a smart choice of weight coefficients that get the best predictions [3 ÷ 8]. Training stops at the moment when it reaches one of the three conditions defined by the user, namely: the maximum time required for training, the number of training cycles or the change of the error at certain time [11].

Assessment of prediction accuracy of neural networks is done by comparing the following parameters [11]:

- Percentage of bad predictions - denotes the number of cases whose predicted value does not match the expected value, i.e. the predicted value is outside the defined margins for tolerance. It is considered that if this value is less than 30 %, the accuracy of the network for predicting the output value is satisfactory.
- Root Mean Square Error - a measure for the deviation of the predicted from actual values. This is one of the most commonly used measures for differences between the provided values by the model and expected values. These individual differences are still called the prediction errors or residual values.
- Mean Absolute Error - the average deviation of predicted from actual values.

Nine multilayered neural networks with forward propagation (MLFN), with one input layer, one hidden layer and one output layer, with different number of neurons in the hidden layer (2 to 10 neurons) were trained and tested and the optimal neural network was defined. Training was conducted through 1 000 000 eras or 1 000 000 cycles of learning. Table 1 shows the results obtained after the testing of all nine neural networks.

If the percentage of bad predictions is within the allowable limits (less than 30 %), then the optimal neural network is the network that has the lowest value of the average error obtained by testing [11]. Analyzing the results shown in Tab. 1 it can be concluded that the worst prediction would be obtained if adopted multifaceted network is with 10 neurons in the hidden layer. Multilayered network with 9 neurons in hidden layer gives the lowest error and therefore this type of network is adopted as the optimal for determination of the fire resistance of analysed columns.

The predicted values obtained by trained neural network for the cases used for training and the calculated values for the fire resistance of the columns, expressed in hours, are compared in Fig. 4.

Table 1 Neural networks testing report

Type of neural network	% bad predictions	RMSE	MAE
MLFN with 2 neurons	0,00	0,39	0,29
MLFN with3 neurons	0,00	0,37	0,28
MLFN with4 neurons	0,00	0,34	0,25
MLFN with5 neurons	0,00	0,38	0,27
MLFN with6 neurons	0,00	0,38	0,27
MLFN with7 neurons	0,00	0,37	0,27
MLFN with8 neurons	0,00	0,38	0,28
MLFN with 9 neurons	0,00	0,32	0,23
MLFN with10 neurons	5,00	2,12	0,69

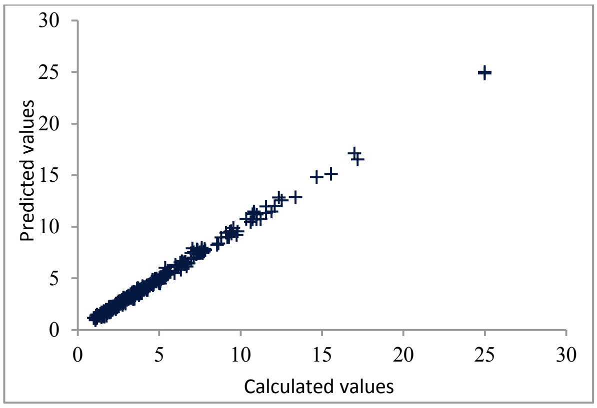

Figure 4 Comparison of calculated and predicted values of the fire resistance of eccentrically loaded columns, used for training the neural network

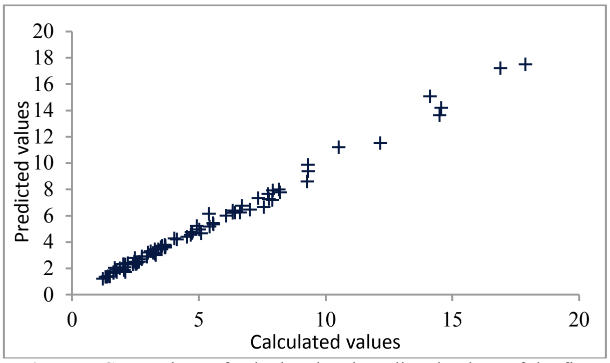

Figure 5 Comparison of calculated and predicted values of the fire resistance of eccentrically loaded columns, used for testing the neural network

The predicted values obtained by the trained neural network for the 80 cases that were not used for the training, but for the testing of the neural network, and the corresponding values calculated with the program FIRE, are compared in Fig 5.

The histogram of the average deviations of the predicted values for the fire resistance of columns used for testing the neural network is presented in Fig 6. Most of the residual values are around 0 which is a good indicator of the accuracy of the model for predicting the fire resistance of this type of columns.

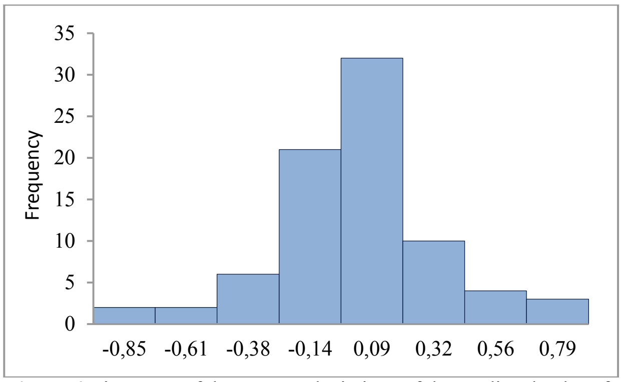

Figure 6 Histogram of the average deviations of the predicted values for the fire resistance of eccentrically loaded columns, used for testing the neural network

Graphical representation of the comparison of the actual (calculated with program FIRE) and the predicted fire resistance values (by using the prognostic model) for 27 cases that were not included in the training and testing process, is given in Fig. 7.

Based on the results obtained from the numerical analysis and the neural network prognostic model, fire resistance curves are constructed [9, 10]. These curves can be used for determination of the fire resistance of RC columns which were not previously analysed. Comparison of the curves for column with dimensions 30×30 cm, concrete cover thickness a = 3,0 cm and percentage of reinforcement μ = 1 %, constructed by both methods, is presented in Fig. 8. From these curves, depending on the level of axial force and bending moment (load coefficient for axial force $-\eta$ and load coefficient for the bending moment $-\beta$), the fire resistance of the column could be defined without any additional calculation.

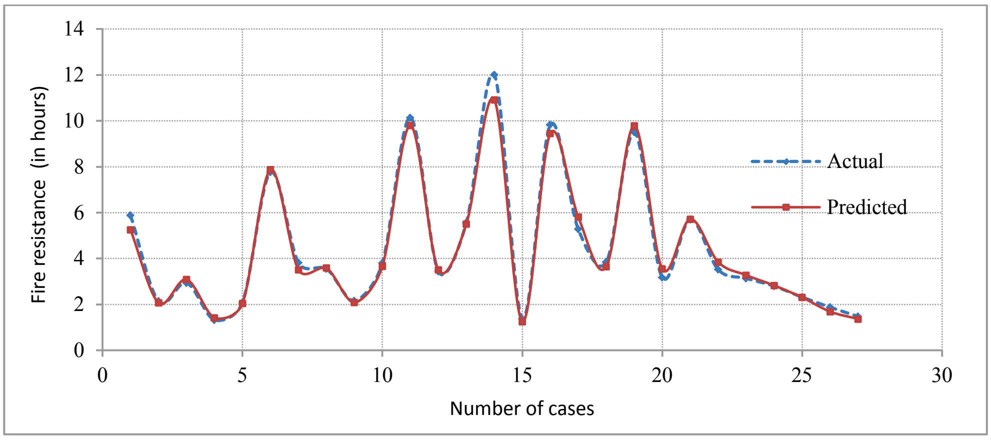

Figure 7 Calculated and predicted fire resistance values for cases that were not included in the training and testing process

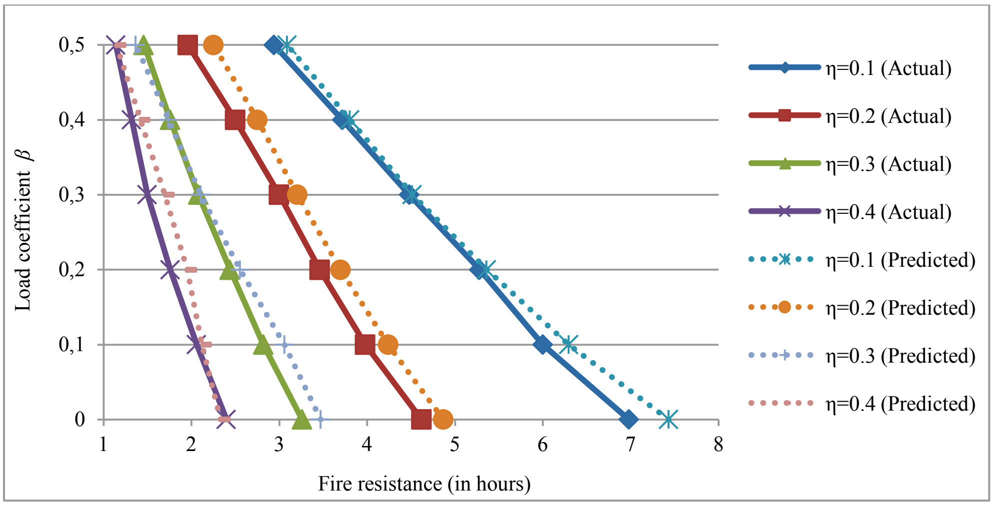

Figure 8 Comparison of calculated (actual) and predicted fire resistance curves for eccentrically loaded RC column with cross section dimensions 30×30 cm, concrete cover thickness a = 3,0 cm and percentage of reinforcement μ = 1 %

It can be seen that the corresponding curves constructed on the basis of the numerically achieved results and on the basis of the results from the neural network approach are similar and give close results.

4 Conclusions

The first known knowledge about neural networks dates from the year 1940, but their practical application began 40 years later with the discovery of appropriate algorithms that significantly increased their applicability and usage. These days there are many research works and continuous interest in neural networks, and they are the subject of studying on many universities worldwide. Neural networks found their practical application in different areas and are used as a method for solving many difficult and complex problems.

Artificial neural networks are one typical example of a modern interdisciplinary subject that helps solving various different engineering problems which could not be solved by the traditional modelling and statistical methods.

The influence of element geometry, concrete cover thickness, steel ratio and intensity of the axial force and the bending moment, as dominant factors that influence the fire resistance of eccentrically loaded columns that are part of a wall for separation of the fire compartment, were analysed and a prognostic model which could generate outputs for the fire resistance of this type of reinforced concrete columns, for any given input data, was build.

Based on the results obtained from the numerical analysis and the neural network prognostic model, fire resistance curves were constructed. It can be seen that the corresponding curves constructed on the basis of the numerically achieved results and on the basis of the results from the neural network approach are similar and give close results. These curves can be used for determination of the fire resistance of RC columns which were not previously analyzed. From these curves, depending on the level of axial force and bending moment (load coefficient for axial force $-\eta$ and load coefficient for the bending moment $-\beta$), the fire resistance of the column could be defined without any additional calculation.

The main goal of this research was to explain the simplicity and the positive aspects of the usage of neural networks for solving engineering problems. After the comparison of numerical methods and neural network's prognostic model it can be concluded that artificial neural networks present an excellent tool for prognostic modelling and can be used for determination of the fire resistance of reinforced concrete columns, especially in those cases when there are no (or very few) experimental and/or numerical results.

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