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# Fire resistance prognostic model for reinforced concrete columns

Marijana Lazarevska, Miloš Knežević, Meri Cvetkovska, Nenad Ivanišević,

Fire-resistance prognostic model for reinforced concrete columns

The prediction model used for defining fire resistance of reinforced concrete columns

exposed to standard fire from all four sides is presented in the paper. The proposed model relies on the concept of artificial neural networks, in which numerical analysis results are used as input parameters. A brief description of the modelling process is given, and an appropriate example of the neural network prognostic model is presented.

#### Autori:

Preliminary note



Marijana Lazarevska M.Sc. CE





Prof. Miloš Knežević, PhD. CE milosknezevic@hotmail.com

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Todorka Samardzioska, Ana Trombeva-Gavriloska

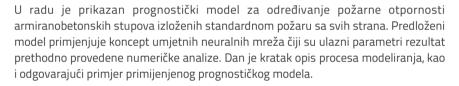
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Prof. Meri Cvetkovska, PhD. CE cvetkovska@gf.ukim.edu.mk

Marijana Lazarevska, Miloš Knežević, Meri Cvetkovska, Nenad Ivanišević, Todorka Samardzioska, Ana Trombeva-Gavriloska

### Prognostički model za određivanje požarne otpornosti AB stupova





Assistant Prof. Nenad Ivanišević, PhD. CE nesa@grf.bg.ac.rs

#### Ključne riječi:

neuralne mreže, požarna otpornost, numerička analiza, AB stup

Vorherige Mitteilung



Associate Prof. <mark>dorka Samardzioska,</mark> PhD. CE samardzioska@gf.ukim.edu.mk



Marijana Lazarevska, Miloš Knežević, Meri Cvetkovska, Nenad Ivanišević,

In der Arbeit ist das prognostische Modell zur Feststellung des Brandwiderstands von Stahlbetonsäulen dargestellt, die bei einem üblichen Brand von allen Seiten ausgesetzt sind. Das vorgeschlagene Prognosemodell verwendet das Konzept künstlicher, neuraler Netze, deren Eingangsparameter Resultat der durchgeführten numerischen Analyse sind. Es ist eine kurze Beschreibung des Modellierungsprozesses sowie ein entsprechendes Beispiel des angewandten prognostischen Modells gegeben.



Assistant Prof. <mark>na Trombeva -Gavriloska</mark>, PhD. CE agavriloska@arh.ukim.edu.mk

## <sup>1</sup>University of Skopje, Faculty of Civil Engineering

#### Schlüsselwörter:

Neurale Netze, Brandwiderstand, numerische Analyse, Stahlbetonsäule

<sup>&</sup>lt;sup>2</sup>University of Podgorica, Faculty of Civil Engineering

<sup>&</sup>lt;sup>3</sup>University of Beograd, Faculty of Civil Engineering

<sup>&</sup>lt;sup>4</sup>University of Skopje, Faculty of Architecture

#### 1. Introduction

Artificial neural networks (further referred to as neural ndi9 53roper det-1.33roper mads -1.33 proper refer.

the stability, quality and use of structures, many countries are nowadays introducing additional regulations concerning the structure's stability and bearing capacity when subjected to fire

In the past, the Republic of Macedonia had no specific regulations aimed at standardizing the design process, as so the control of structure's behavior during fire was also largely unregulated. However, the fast engineering development and the dominance of high structures imposed to the need to devise stricter requirements regarding stability of structures and their safety when exposed to fire. The implementation of Eurocodes as national standards is an ongoing process in Macedonia, which will certainly bring positive developments in that direction.

The legally prescribed time period in which a structure must remain stable and safe under fire is expressed as time in minutes, and this time 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 occupancy of the structure, the distance to fire stations and fire brigades, and the fire protection system of the structure [10].

The fire resistance of a structure can be determined based on the estimated fire resistance of the entire structure, or of each of its structural elements (columns, beams, slabs, walls etc.). The fire resistance of a structural element is the time period (in minutes) from the start of fire to the moment when the element attains its ultimate capacity (ultimate strength, stability and deformability), or to the moment when the element loses its separating function.

The basic requirement for fire resistance of structures and/or their elements is expressed as follows (Eq. 1):

$$t_{p} \le t_{u} \tag{1}$$

Where: " $t_{\rho}$ " represents the legally prescribed fire resistance of structure (rank of fire resistance) and " $t_{\nu}$ " s an experimentally or analytically estimated fire resistance according to the standard fire test.

The legally prescribed fire resistance can be achieved by applying various structural measures (proper form, element's dimensions and static system), or by adopting special protection measures (thermal insulation, etc.). Although many protection measures are currently available, the final choice mainly depends on the type of construction material that needs to be protected. Individual construction materials (concrete, steel, wood) exhibit different behaviour under elevated temperatures, which is why they have to be treated in accordance with their individual characteristics when exposed to fire [10, 11].

Even though the legally prescribed fire resistance is of huge importance for the quality and safety of every structure, the Republic of Macedonia has still not developed a legally binding regulation for fire resistance. This is an enormous downside that should be remedied in the near future.

# 2.2. Determining fire resistance of RC columns – Numerical analyses

Numerical analyses aimed at defining behaviour of centrically loaded reinforced concrete columns exposed to standard fire test, from all four sides, were conducted on Faculty of Civil Engineering in Skopje [10]. The computer program FIRE (FIre REsponse) was developed as a result of her research. This program is capable of predicting nonlinear response of reinforced concrete elements and plane frame structures subjected to fire. The program analyzes the nonlinear transient heat flow (module FIRE-T), and the nonlinear stress-strain response associated with fire (modulus FIRE-S). The technique used in FIRE is the finite element method coupled with the time step integration.

Using the program FIRE, the behavior of centrically loaded columns exposed to standard fire according to ISO 834 (recommended in Eurocode 1, Part 1.2) was analyzed, and the influence of element geometry, concrete cover thickness, type of aggregate, concrete grade, steel ratio, and axial force intensity, was defined. In this case, the support conditions and column length have a negligible influence on fire resistance, and were therefore not varied [5, 10].

The model of the RC column subjected to analysis is presented in Figure 1. The column was exposed to standard fire from all four sides of the cross section, and the following support conditions were adopted: fixed at the bottom side and freely supported at the top side, which allows free expansion in the longitudinal direction.

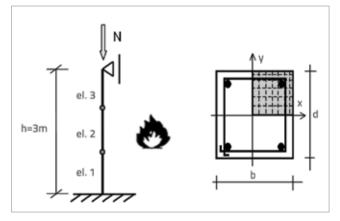


Figure 1. Reinforced-concrete column exposed to standard fire from all four sides

The analyses were conducted for different values of the axial force N, and for different cross sectional dimensions of the columns (20x20, 30x30, 40x40, and 50x50). The protective concrete layer thickness varied from 2 to 4 cm, and the loading coefficient  $\alpha$  ranged from 0 to 0.5 ( $\alpha$ =N/N<sub>ult</sub> where N is the applied axial force and N<sub>ut</sub> is the ultimate axial force for the same column).

Fire resistance curves were defined based on numerical analysis results [5, 10]. These curves can be used to determine fire resistance of RC columns which were not previously subjected to numerical analysis. Some of these curves are presented below, and compared to the curves obtained using the neural network prediction model.

## 2.3. Determining fire resistance of RC columns - Neural network prognostic modelling

The application of neural networks to build a prognostic model that can be used for predicting fire resistance for structures and/or their elements is of huge importance for the design process in construction. Most experimental models for determining fire resistance are extremely expensive, and analytical models are quite complicated and time consuming. That is why modern analyses, such as the modeling through neural networks, can be of great help, especially in cases when some prior analysis results are available. The goal of the research presented in this paper is to build a prognostic model that can generate outputs for fire resistance of centrically loaded reinforced concrete columns (further referred to as RC columns) for any given input data, by using numerical results from the research program of Cvetkovska, as input data [10]. In the first step, the mathematical model for the neural network with defined inputs (data for the dimensions of the cross section, percentage of reinforcement, thickness of the protective concrete layer, aggregate type, and the external loading level) is set up, and available data are used to train an appropriate network. After the training process, the neural network is tested for any input data (differing from those used in the training process) and the results generated in this way are compared.

The first step of the modeling process is to define architecture of the neural network and to select input parameters [12, 13]. The following input parameters are used for this engineering problem: column dimensions (b and d), concrete grade ( $f_c$ =25 Mpa and  $f_c$ =35 Mpa), protective concrete layer thickness (a), percentage of reinforcement ( $\mu$ ), loading coefficient ( $\alpha$ ), and aggregate type (S-silicate and C-carbonate). However, the numerical analyses conducted using the computer software FIRE, and the prediction model made by neural network, show that the concrete grade (FC25 or FC35) has an insignificant influence on the fire resistance of RC columns [5, 10]. That is why this parameter was omitted from the analysis. The neural network was trained using the following input parameters:

column dimensions, concrete layer thickness, reinforcement percentage, aggregate type, and loading coefficient.

The output parameter of the neural network model is the fire resistance of the RC column, and it is expressed as time in hours (t). A multilayer non-recurrent neural network (with one input layer, two hidden layers, and one output layer) was chosen for training of the network (Fig. 2). Each hidden layer has 12 neurons inside.

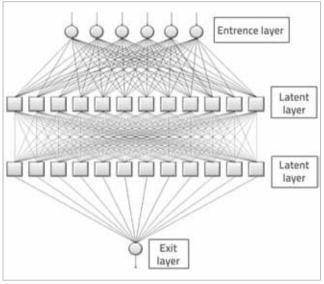


Figure 2. Neural network model used for analyzing fire resistance of RC columns

A logistic sigmoid function was used as the activation function (Eq. 2) [12, 13].

$$f(x) = \frac{1}{1 + e^{-x}} \tag{2}$$

The neural network was trained with an improved "backpropagation" algorithm (data from the training group were periodically transmitted through the network) [12 - 15]. Actual output data were compared with the expected ones. In cases when a difference between the data was registered, the weight coefficients were adjusted using the procedure described in references [12, 13].

The network training process was conducted via 500 epochs (500 learning cycles). The training was realized using a specialized computer software operating under MS Excel [12, 13]. 104 groups of input data were used for network training. Ten of them (about 10 percent) belonged to the validation data group. At the beginning of the training process, the output values differed from the expected ones. However, after the training, the network started to generate more accurate results. In order to check the quality and accuracy of the network, control tests were also performed. The network was tested using 10 different

data groups, consisting of data which had not been used during the learning and training process. The results of this testing were excellent

### 3. Comparative analyses of results

The result of this research is the predicted fire resistance of reinforced-concrete columns, expresed in hours. The fire resistance values obtained using the computer software FIRE (numerical analyses), and the results generated from the trained neural network, were compared. Both values were almost identical, and so it can be concluded that neural networks are excellent when used as prediction models. Some of fire resistance values generated via the computer software FIRE (numerical analyses), and the results generated from the trained neural network, are shown in Table 1:

The results shown in Table 1 demonstrate that, when using the input data from the training data group, neural networks can generate very precise values for the fire resistance of reinforced-concrete columns exposed to fire on all four sides. The control test had to be performed in order to check the network quality and accuracy. The neural network was tested using 15 different data groups, consisting of data which had not been used in the learning and training process. The testing gave excellent results. The comparison is presented in Table 2:

A simpler approach is to compare fire resistance curves obtained from both analyses (numerical and neural networks). The fire resistance curves obtained from numerical analyses and via the neural network modeling are presented in Figures 3, 4, 5, and 6. These curves show influence of input parameters (column dimensions, concrete layer thickness, reinforcement percentage, aggregate type, and loading coefficient) on the output result (fire resistance in hours).

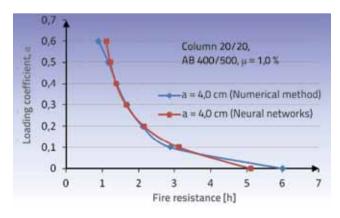


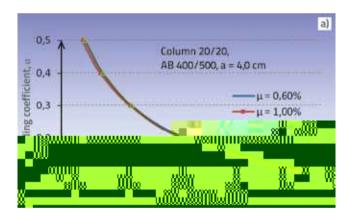
Figure 3. Comparison of fire resistance curves obtained by both methods, when protective concrete layer thickness is  $\alpha \! = \! 4.0 \; \mathrm{cm}$ 

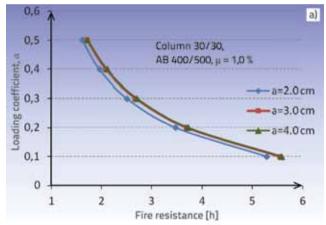
Table 1. Overview of results generated via computer software FIRE, and using the neural network prediction model (training data groups)

			OUTPUT DATA (fire resistance in hours)				
Column dimensions [cm]		Protection layer thickness [cm]	Reinforcement percentage [%]	Type of aggregate S - silicate C - carbonat	Loading coefficient	Numerical method	Neural network
Ь	d	a	μ	S or C	α	t	t
20,0	20,0	2,0	1,0	S	0,1	2,825	2,798
				S	0,4	1,261	1,257
				S	0,5	0,956	1,132
	20,0	2,0	0,6	S	0,1	2,845	2,784
				S	0,2	2,085	1,912
20,0				S	0,3	1,.615	1,495
				S	0,4	1,285	1,273
				S	0,5	0,965	1,144
		3,0	1,0	С	0,1	3,65	3,485
				С	0,2	2,7	2,650
20,0	20,0			С	0,3	2,125	2,136
				С	0,4	1,725	1,773
				С	0,5	1,375	1,493
		4,0	1,5	S	0,1	2,91	3,116
	20,0			S	0,2	2,115	2,072
20,0				S	0,4	1,435	1,322
				S	0,5	1,224	1,176
20,0	20,0	5,0	1,0	S	0,1	2,84	2,957
				S	0,2	2,09	2,045
				S	0,3	1,61	1,601
	30,0	3,0	1,0	С	0,1	6,3	6,682
				С	0,2	4,75	4,848
30,0				С	0,3	3,75	3,602
				С	0,5	2,05	2,096
	30,0	4,0	1,0	S	0,2	3,74	3,724
30,0				S	0,4	2,255	2,110
				S	0,5	1,72	1,729
	40,0	3,0	1,0	С	0,1	9,65	9,496
				С	0,2	7,25	7,663
40,0				С	0,3	5,725	5,703
				С	0,4	4,375	4,148
40,0	40,0	4,0	1,0	S	0,1	7,95	8,181
				S	0,2	5,775	5,833
				S	0,3	4,35	4,188
				S	0,4	3,45	3,196
				S	0,5	2,5	2,558
50,0	50,0	2,0	1,0	S	0,1	9,55	9,712
				S	0,2	7,95	8,078
				S	0,3	6,15	6,041
				S	0,4	4,35	4,447

Table 2. Overview of results generated by the computer software FIRE and the neural network prediction model (testing data groups)

			OUTPUT DATA (fire resistance in hours)				
dimer	umn nsions m]	Protection layer thickness [cm]	Reinforcement percentage [%]	Type of aggregate S - silicate C - carbonat	Loading coefficient	Numerical method	Neural network
b	d	a	μ	S or C	α	t	t
20	20	4	0,60	S	0,20	2,105	1,987
20	20	4	1,00	S	0,40	1,395	1,329
20	20	2	1,50	S	0,10	2,810	2,873
20	20	5	1,00	S	0,40	1,270	1,354
30	30	3	1,00	S	0,20	3,710	3,695
30	30	3	1,00	С	0,40	2,975	2,731
40	40	2	1,00	S	0,20	5,675	5,617
40	40	3	1,00	С	0,50	2,925	3,024
50	50	3	1,00	С	0,40	5,800	5,706
50	50	3	1,00	С	0,20	8,150	8,189





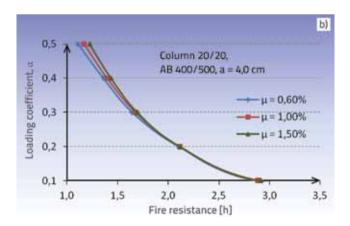


Figure 4. Fire resistance curves for different reinforcement percentages, obtained by both methods: a) neural network, b) computer software FIRE

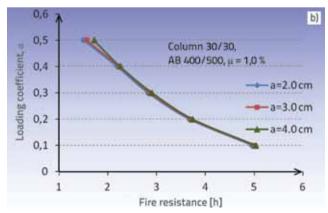
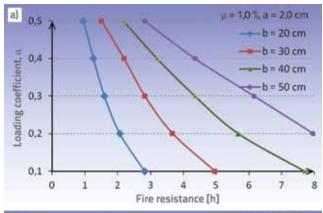


Figure 5. Fire resistance curves for different thickness of the protection concrete layer, obtained by both methods: a) neural network, b) computer software FIRE



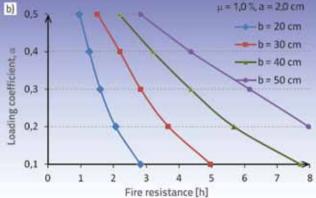


Figure 6. Fire resistance curves for different column dimensions, obtained by both methods: a) neural network, b) computer software FIRE

It can be seen that the curves based on numerical results are quite similar to those based on the neural network approach.

The main goal of this research was to explain the simplicity and positive aspects of neural networks when used as a means to solve engineering problems. After the comparison of the two methods, it can be concluded that artificial neural networks are an excellent tool for prognostic modeling, and that they can be used for determining fire resistance of reinforced concrete columns, especially in those cases when there are no (or very few) experimental and/or numerical results.

#### 4. Conclusion

Although the first information about neural networks dates back to 1940, their practical application begun only four decades later, after discovery of appropriate algorithms which significantly increased their applicability. A lot of research is currently conducted in the sphere of neural networks, and these networks are increasingly studied at many universities all over the world. Neural networks are an example of a sophisticated modeling technique, and they have found their practical application in different areas, namely as a method for solving a variety of difficult and complex engineering problems.

The application of neural networks for prognostic modeling aimed at predicting fire resistance of structures and/or their elements is highly significant for the construction design process. Most experimental models for fire resistance determination are extremely expensive, while analytical models are quite complicated and time consuming. That is why a modern type of analysis, such as modeling based on neural networks, can be considered as extremely helpful, especially in cases when some prior analyses had already been made.

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