Neural Networks Applicability for Design of Reinforced Concrete Sections for Bending

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***Abstract* – Solving engineering design tasks requires the use of analytical formulas and dependencies. The direct inclusion of mathematical expressions in the artificial neural network (ANN) is not possible. This research studies the possibility of applying the neural networks method for designing of single or double-side reinforced concrete sections. A Visual Basic for Applications (VBA) macro was developed in the MS Excel environment to solve the task of determining the required area of the reinforcement by given geometric dimensions and bending moment and applying classical analytical formulas for reinforced concrete sections design. The training of the pre-configured neural network is performed by approximately 34000 sets of matching input parameters. The presented results from the trained ANN are compared and analysed against the exact analytical solutions. The study presents an approach to the application of structural design calculations. The results suggest that the approach is applicable to more complicated structural design problems.**

***Keywords* – Neural networks, reinforced concrete section design.**

1. Introduction

The aim of the study is to show the applicability of the artificial intelligence method in dimensioning of reinforced concrete elements.

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The current research is focused on the application of neural networks to civil engineering calculations as in study [3]. The design of columns loaded axially under uni-axial bending and the design of simply supported singly reinforced beams are done [4]. Afaq Ahmad *et al.* [4], considered the problem of evaluation of reinforcement beam subjected to plane bending. Similar research is made by Sangeetha P. *et al.* [5] on the effects of external influences in reinforced concrete elements. This study uses neural networks with error backpropagation algorithm. In Pendharkar U. *et al.* [1], a neural network with two inner layers with 6 and 11 neurons, respectively, and one output neuron was used. A continuous reinforced concrete beam is modelled with 6 structural parameters, which are given at the input, and as a result, the ratio between the elastic and inelastic moment of the beam section in the output neuron is calculated. A similar study by Hadi, M.N.S. *et al.* [2] on the model of a reinforced concrete beam, subjected to in-plane bending used a neural network with a training set (input - output data) of 500 samples. The set involves 5 input values - the geometric data of the reinforced concrete section b and h, bending moment M and concrete compressive strength and steel tensile strength. The values for concrete and reinforcement strengths in the present study are assumed to be constant. In the study carried out in [2], the optimal cost of the section was sought using 4 output parameters – optimal percentage of reinforcement, optimal grade of steel, optimal height from the centre of the reinforcement to the upper edge of the section d and the monetary cost of the section. In present study the objective is establishing the required area of the longitudinal reinforcement. The above comparison is to emphasize that despite the complexity of the problem on the one hand in [2] relatively few inputs (500) were used, while in the present study the number is 37400, using only one additional inner layer besides the one for the input values consisting of 10 neurons. In the current study on the dimensioning of rectangular reinforced concrete sections according to Eurocode 2-1 [7] and national annex [10].

The recommendations in [8], [9] and the design guidelines in [11], [12], and [13] were used for preparing and confirming the correctness of the training set. A rectangular reinforced concrete cross-section, reinforced on both sides, subjected to plane bending is considered in Figure 1.

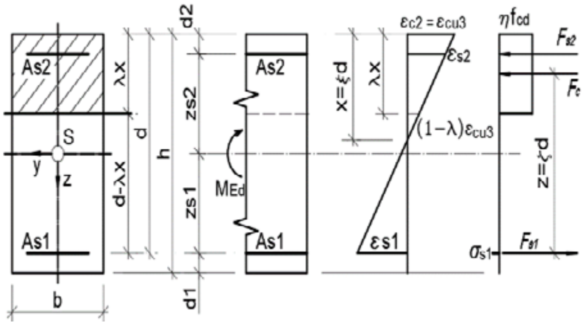

Figure 1. Dimensioning of reinforced concrete rectangular section subjected to plane bending

In Figure 1, Fs_1 denotes the force in the tension reinforcement, Fs_2 – the force in the compression reinforcement, Fc – the force in the concrete, d and b are the height and width of the reinforced concrete section, respectively, M_{Ed} is the calculated value of the bending moment.

The calculations were performed by a Microsoft Excel VBA macro.

2. Data Generation

The methodology given in [5] and [6] was used for designing the reinforced concrete section.

2.1. Neural Network Description

The adopted input data were generated as follows: the section width b varies from 15 to 40cm in step sized 2cm, the section height h varies from 25 to 80 cm in step of 2cm, the width and height values that are multiples of 5cm are also added. The bending moment M is evaluated by a VBA Excel macro built for the purpose: for each section, the bending moment capacities of single side reinforced concrete section $M_{Ed,lim}$ and double-sided reinforced section $M_{Ed,max}$ are calculated. The step value is defined in dividing the intervals into 25 equal parts. After reaching the value of $M_{Ed,lim}$, the bending moment M is increased and the respective upper (As_2) and lower (As_1) reinforcements are calculated. The calculations continue until reaching r = 2.85 %, where r is the value of the reinforcement coefficient for the section. In this way were generated 37400 data sets of the input parameters b, h, M and the target values - As_1 and As_2.

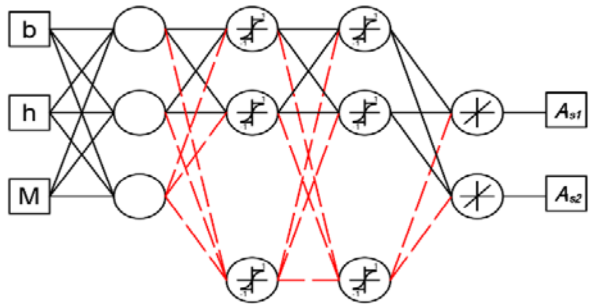

Figure 2. Schematic of the neural network used

A significant number of examples showing the application of artificial intelligence in various fields and particularly in construction have been presented nowadays. Most often self-made software products were developed and in some cases by using available commercial programs, a number of calculations are performed. After that a neural network is defined and trained by using the generated sets. The neural network establishes the sought interpolation dependence. Neural networks consist of an input layer, an output layer, and one or more intermediate layers. In this study the neural network is created by using the Deep learning toolbox in Matlab [14] software. The results were obtained for a neural network with two internal layers connected by tan sigmoidal transfer function.

There are two neurons corresponding to the resulting values for lower and upper longitudinal reinforcement areas As_1 and As_2. A linear transfer function PureLine() is assigned to them. The Levenberg – Marquardt algorithm is used for training the neural network.

2.2. Input Data for the Neural Network

Neural networks are trained by feeding one or more input vectors at the input and their corresponding value for the output - a target vector (in this study, two output vectors are set at the output). Each of the neurons has input parameters: weights and offsets, and a result that it passes to the next layer or to the output. The neural network is "trained" by changing the parameters of the neurons, located in neighbouring layers. One complete cycle of matching all inputs to the target vector is called an epoch.

It is necessary to make a series of solutions with different configurations of neural networks because there is no direct relationship between the number of hidden layers, the number of neurons in them, and the epochs. After a series of trials, a neural network composed of three layers was adopted for the available data – shown in Figure 2.

The type of the Target Vector As_2 predefines the complications of the studied problem. In accordance with the preliminary expectations, for 55 % of the data it has a value of zero – the bending moment is fully absorbed by the bottom reinforcement.

This is followed by normalization of the input parameters and of the target vectors.

$$k_n = -1 + 2\frac{k - k_{\min}}{k_{\max} - k_{\min}} \qquad (1)$$

where k is the current value for the corresponding quantity which dimensions and names are listed below:

b - current section width, cm;

h - current section height, cm;

M - the bending moment applied in the section plane, kNm;

As_1 – the bottom longitudinal reinforcement area for the section with dimensions b and h, designed for the bending moment M;

A_{s2} – the top longitudinal reinforcement area for the section with dimensions b and h, designed for the bending moment M.

The neural network training is processed with the thus normalized input and output data.

2.3. Adopted Neural Network Configurations for the Study

There is no empirical dependence for constructing a neural network for solving a given problem. In principle, more complex and complicated tasks accompanied by large quantities and data require larger number of neurons and more internal layers. This study examines these approaches.

The considered models have two inner layers that correspond to the complexity of the task.

The first outer layer is connected to the input data, and the second outer layer is connected to two neurons for the output quantities A_{s1} and A_{s2}. The inner layers are located between the outer layers. Each neuron has a transfer function that transforms its input value to the respective input value of the corresponding neuron from the next layer.

Tan sigmoidal transfer function is used for the neurons from the two inner layers:

$$a = \text{tansig}(n) = \frac{2}{1 + e^{-2n}} - 1$$

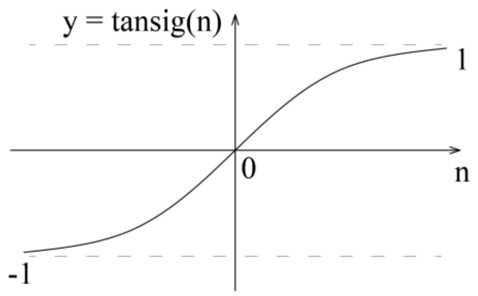

Figure 3. Tansigmoidal transfer function

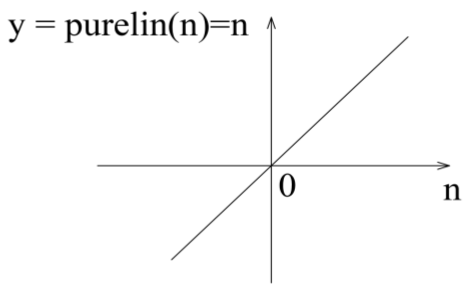

Figure 4. Purlin transfer function

The transfer function for the two neurons in the output layer is linear "purelin()" as shown in Figure 4.

The number of neurons in the inner layers changes as follows: from 6 to 20 with step of 2 for the first inner layer and from 6 to 18 for the second layer. A total number of 56 neural networks were trained with these neurons.

In Figures 5 and 6 the results from training of the neural networks with 2 internal layers and 10 neurons in each of them are shown.

The obtained trendlines indicate that the neural network is well trained. This is based on the result for the R value above 0.998 for

- Training
- Validation
- Test
- All values

The neural networks applicability to solving structural design tasks is assessed by comparison of the results to the solution obtained in [5] that was not used in the neural network training set and generated for the same parameters. The relative error between the two above solutions is less than 0.001. The results are shown in tabular form.

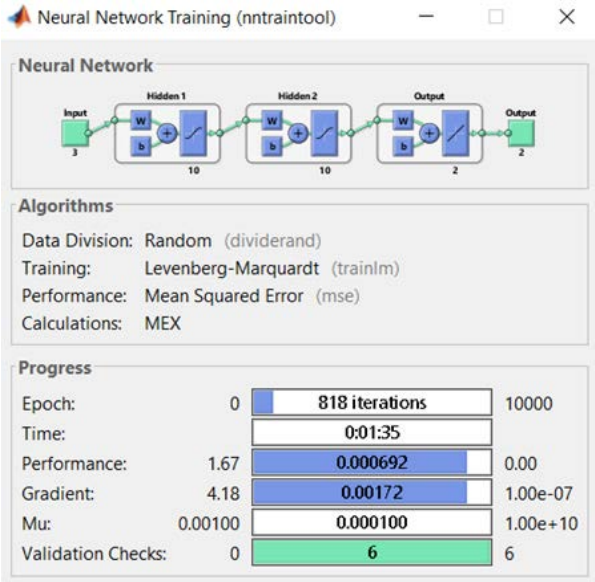

Figure 5. Schematic of training neural network in real time

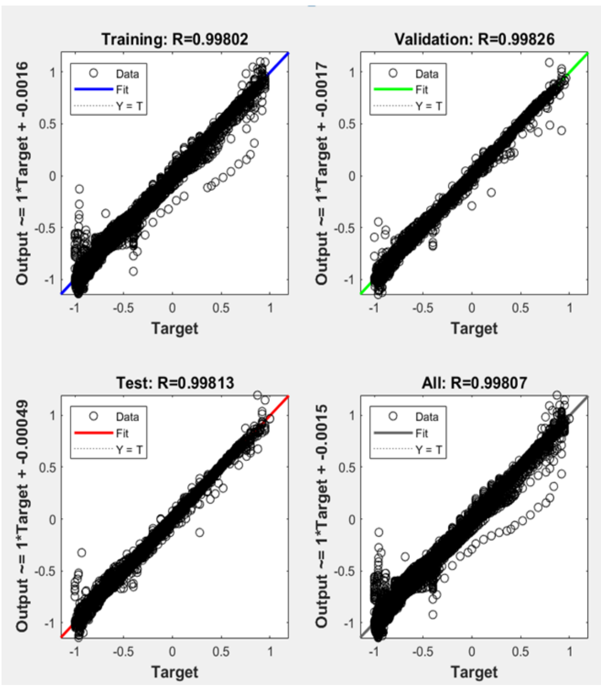

Figure 6. Regression of trained neural network

The next two tables show the relative errors in percent for the upper A_{s2} and lower A_{s1} reinforcement areas obtained after denormalization of the values from the two output neurons in the output layer.

The denormalization formula is:

$$k = \frac{k_n + 1}{2}(k_{max} - k_{min}) + k_{min} \qquad (2)$$

Table 1. Relative error for lower reinforcement area A_{s1} in percent

Err (A_{s1}) [%]		No of neurons in the 2-nd internal layer						
		6	**8**	**10**	**12**	**14**	**16**	**18**
No of neurons in the 1-st internal layer	**6**	-0,8	-0,7	1,3	0,2	-2,3	2,9	-1,6
	8	-1,4	-0,5	-3,0	-1,5	-0,1	-0,6	1,2
	10	1,6	-1,3	0,1	-0,4	-2,2	1,2	-1,8
	12	-2,7	-3,0	-0,8	-1,0	0,0	1,0	-2,0
	14	-2,6	1,4	0,6	-3,1	-1,5	0,0	-1,0
	16	1,3	0,0	1,2	-1,1	0,1	1,2	-1,3
	18	1,5	-0,9	0,7	0,2	-0,5	0,4	-1,4
	20	-1,1	0,2	-0,9	-2,2	-1,2	-3,0	0,0

Table 1 shows that the smallest relative error is observed for neural networks with 12 to 16 neurons in the first internal layer and respectively 14 to 18 neurons in the second internal layer.

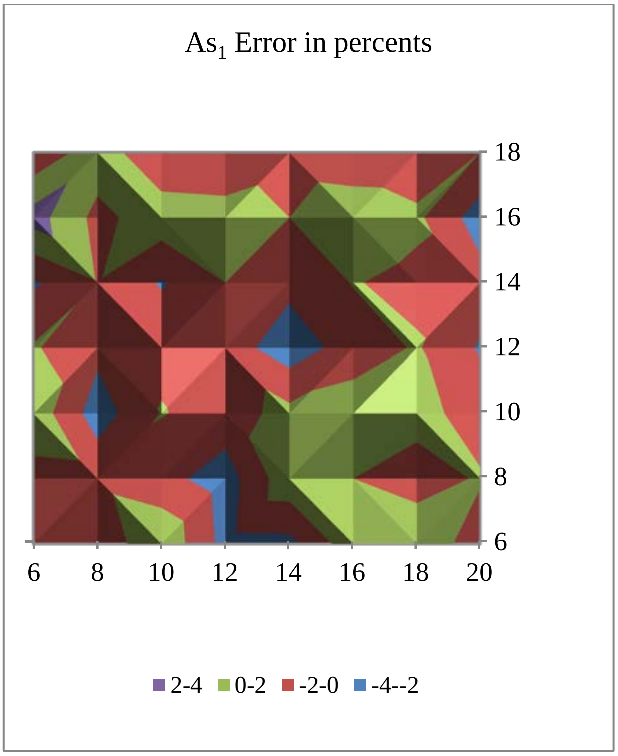

Figure 7. Surface contour of the percent error of A_{s1}

The results are graphically displayed in in Figures 7 and 8. In Table 2 the smallest absolute value of the relative error is observed at neural networks with 12 neurons in the first internal layer and respectively with 10 and 16 neurons in the second internal layer.

Based on the above observations of the relative errors for upper (As_2) and lower (As_1) reinforcement areas the configuration with 12 to 16 neurons in the first and 16 neurons in the second internal layer is the optimal one.

Table 2. Relative error for upper reinforcement area A_{s2} in percent

Err **(A_{s2}) [%]**		No of neurons in the 2-nd internal layer						
		6	**8**	**10**	**12**	**14**	**16**	**18**
No of neurons in the 1-st internal layer	**6**	3,7	4,1	-4,3	3,2	-0,5	0,7	3,5
	8	2,4	-4,2	-2,4	-2,8	-4,2	4,2	1,2
	10	1,4	-0,8	3,7	-1,2	-0,6	-0,8	-1,4
	12	-3,5	3,5	-0,1	-2,9	-3,3	0,2	1,4
	14	-2,5	-2,2	-1,4	4,7	-1,5	-2,5	0,8
	16	0,6	-2,5	3,3	1,8	-2,8	-4,1	1,3
	18	-1,9	0,2	3	-0,5	-2,1	-2,9	0,7
	20	0,9	2,6	3,7	-1,9	-0,6	1,5	3,4

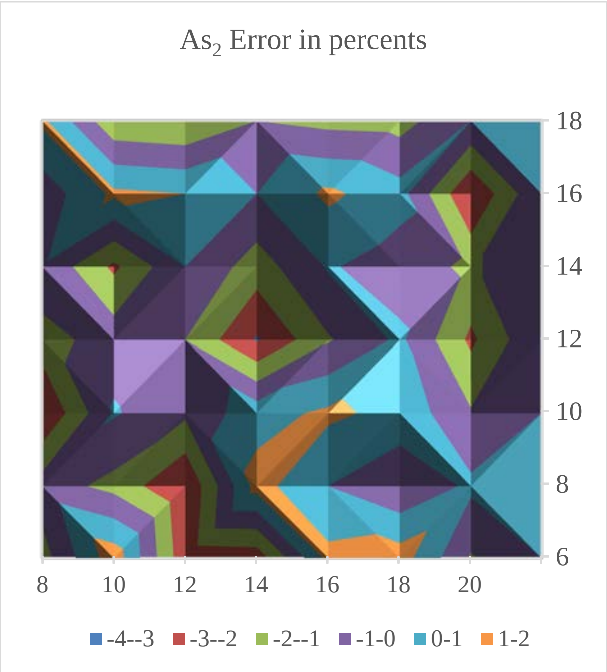

Figure 8. Surface contour of the percent error of A_{s2}

3. Conclusion

The results from the current study confirm the prospectivity of the application of artificial neural networks as an alternative to the analytical numerical approach to design of reinforced concrete structural sections. The study demonstrates an approach for assessing the dependency on the precision of results from ANN on the number of neurons in the internal layers.

The ability of ANN to conduct nonlinear function interpolation is used. This paper presents a study of the accuracy of designing a rectangular reinforced concrete section with single and double- side reinforcement, subjected to in- plane bending moment, according to EuroCode 2 [7] and [10], by ANN.

The neural networks are appropriate for obtaining results for phenomena described by nonlinear equations as well as for establishing dependencies between input and output values of numerical models. The study confirms the applicability of neural networks as an alternative to the deterministic engineering design calculations. The evaluated percentage error in the reinforcement area results for each of the 56 ANN's containing different number of neurons in their internal layers satisfies the practical precision requirements for the considered design problem and demonstrates that there is no direct dependence between the number of the neurons in the internal layers and the solution precision.

Further research is necessary for establishing the optimal ANN set with minimum combined number of neurons for designing reinforced concrete sections for varying concrete classes, under the interaction of in- and out- of plane bending moments and axial force and different section geometries. This study is the first step in the constructing the optimal ANN, capable to replace the traditional algorithms for design of reinforcement concrete sections.

References:

[1]. Pendharkar, U., Chaudhary, S., & Nagpal, A. K. (2007). Neural network for bending moment in continuous composite beams considering cracking and time effects in concrete. *Engineering structures*, *29*(9), 2069-2079.

[2]. Hadi, M. N. (2003). Neural networks applications in concrete structures. *Computers & structures*, *81*(6), 373-381.

[3]. Chandan, M. K., Raghu, P. B., & Amarnath, K. (2017). Design of reinforced concrete structures using neural networks. *International Research Journal of Engineering and Technology (IRJET)*, *4*(7), 2395-0056.

[4]. Ahmad, A. (2018). *Reinforced Concrete (RC) Structures Analysis and Assessment with Artificial Neural Networks (ANNs)* [Doctoral dissertation, Heriot-Watt University].

[5]. Sangeetha, P., & Shanmugapriya, M. (2020, December). Artificial neural network applications in fiber reinforced concrete. In *Journal of Physics: Conference Series*, *1706*(1), 012113. IOP Publishing.

[6]. Kaczmarek, M., & Szymańska, A. (2016). Application of artificial neural networks to predict the deflections of reinforced concrete beams. *Studia Geotechnica et Mechanica*, *38*(2).

[7]. Code, P. (2005). Eurocode 2: design of concrete structures-part 1–1: general rules and rules for buildings. British Standard Institution, London, 668, 659-668.

[8]. Rusev, K. & Yancev Vl. (2008). Orazmeryavane na pravoŭgŭlni stomanobetonni secheniya, podlozheni na ogŭvasht moment po Evrokod 2 (edinichna armirovka). *Stroitelstvo* , *4*, 2-10.

[9]. Rusev, K. & Yancev, Vl. (2008). Orazmeryavane na pravoŭgŭlni stomanobetonni secheniya, podlozheni na ogŭvasht moment po Evrokod 2 (dvoĭna armirovka). *Stroitelstvo, 5*, 9-14.

[10]. BDS EN 1992–1-1/NA (2011) *Eurocode 2: Design Of Concrete Structures - Part 1-1: General Rules And Rules For Buildings. National annex (NA).* BIS.

[11]. Rusev K et al. (2013). *Evrokod 2, Rykovodstvo po stomanobeton.* Sofia: Kamara na inzhenerite v investitsionnoto proektirane.

[12]. Rusev K., Kardjiev V. (2016). *Evrokod 2, Rykovodstvo po stomanobeton. Dopylnenie kym pyrvo izdanie.* Sofia: KIIP.

[13]. Kardjiev V., Hristov P. (2016). Harakterni osobenosti pri izchislqwane na krygli stomanobetonni koloni , podlojeni na ogyvane s normalni podlojeni na ogyvane s normalni natiskovi sili. *First scientific – applied conference with international participation: Reinforced concrete and masonry structures – theory and practice*, Annual of UACEG. Sofia.

[14]. Beale, M. H., Hagan, M. T., & Demuth, H. B. (2010). *Neural network toolbox*. User's Guide, MathWorks, 2, 77-81.