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A PRELIMINARY ESTIMATE OF TIME AND COST IN URBAN ROAD CONSTRUCTION USING NEURAL NETWORKS

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Professional paper
Business carried out by construction companies is based on the implementation of agreed projects within the agreed cost and time limits. The contractor's estimation of a project goes through several phases. A preliminary estimate of the duration and cost of a construction is essential and is the first phase of the estimate, in fact, it is one of the most important phases considering that it is the basis for any decision concerning involvement in the potential project. The contractor's reply to the investor regarding involvement in the potential project must be submitted on time, it must be accurate enough and with the minimum cost invested in the analysis. Analyses conducted within the research presented in this paper confirm that artificial neural networks (ANN) offer the possibility of satisfying all three criteria. That is, ANNs provide satisfactory accuracy for the preliminary estimate of the duration and cost of projects with the minimum engagement of resources to implement the above analysis.

Keywords: *artificial neural networks, cost and duration estimation, normalization, road construction*

Preliminarna procjena vremena i troškova izgradnje gradskih prometnica primjenom neuronskih mreža

Stručni članak
Realizacija projekata u okviru definiranih vremenskih rokova i ugovorenih troškova predstavlja osnovu za uspješno poslovanje izvođačkih građevinskih poduzeća. Odluka pojedinog poduzeća o sudjelovanju u projektu zasniva se prvenstveno na preliminarnoj procjeni potrebnog vremena i troškova za izgradnju projektom definiranog objekta. Investitor navedenu odluku očekuje unutar postavljenog roka uz realnu procjenu kako troškova tako i vremena, pri čemu napori izvođača uloženi u potrebne analize trebaju biti minimalni. Istraživanje provedeno u sklopu ovog rada upućuje da umjetne neuronske mreže (ANN) omogućavaju provođenje opisanih analiza uz zadovoljenje prethodno navedenih kriterija. Odnosno, potvrđeno je da ANN omogućavaju dovoljno točne preliminarne procjene vremena i troškova tijekom izvođenja radova uz minimalno korištenje uobičajeno potrebnih resursa.

Ključne riječi: *izgradnja gradskih prometnica, normalizacija, procjena troškova i vremena, umjetne neuronske mreže*

1 Introduction

The business success of construction companies is based on the realization of agreed projects within the agreed duration and for the agreed price. The main precondition for this is the extensive consideration of the project at all the stages of its implementation. When doing so, special attention should be paid to the beginning, i.e., before agreeing on the terms of the contract. In order to determine whether it is acceptable to the contractor to take on the potential project, it is necessary to analyse two basic parameters, the cost and duration, which is all done while still at the pre-contract stage with a view to making a decision about possible involvement in the project i.e., by making an offer.

The contractor's assessment of the cost and duration of the project begins with receiving a query from an investor and takes place in several stages [1]. Cost estimates evolve through preliminary or conceptual phases into detailed, final or definitive estimates, depending on the amount of information known when the estimate is prepared [2]. Estimating the time required to realize the project also goes through these phases. Quite often, the query regarding the potential work contains the minimal amount of information, and on the basis of this, the contractor should make an estimate before making an offer [1, 2]. Prior to making an offer for the completion of a project, a preliminary or conceptual estimate is made, which should be completed as soon as possible after receiving the query from the investor. A detailed analysis of the potential project in terms of cost, also taking into consideration the amount of time required, can be very high (from 0,25 to 1,00 % of the total estimated value of the work) depending on the amount of work involved [3].

Experience has shown that there is very often a discrepancy between the estimated duration and cost of a project and its final cost and duration, which, by definition is when the project is totally completed. This fact implies that it is very useful for companies to form internal databases which can later be used for estimating future projects. It is necessary to enter data into the database from the initial query and project documentation from the investor, along with the tender price and project deadline, but also the real cost and duration of the project. Such a database would greatly facilitate the formation of a preliminary estimate for a potential project. A preliminary estimate has the task of evaluating the validity of the potential project, that is, to decide whether to put in an offer for carrying out the work at all. Considering that when forming a preliminary estimate the contractor has such sparse information about the job itself, the use of modern prediction methods is very valuable, and one such method is the use of neural networks.

The application of neural networks when forming a preliminary estimate, to a significant extent, would reduce the time and with that the cost of data processing. Use of a database, in which the assessment of the potential viability of a project uses historical data on the real cost and realization time of completed projects, would make a more accurate estimate of the duration and cost of a potential project and therefore make the contractor's decision regarding possible involvement in the project much easier.

The aim of the research shown in this paper is to form, with the help of ANN, an integrated model for the preliminary estimation of the real cost and duration for urban road construction and associated landscaping. The formation of an integrated model implies that a prediction is made at the same time for both the duration and cost on the basis of the same data input. Given that these are preliminary estimates of the mentioned parameters, the main data on the basis of which it is possible to make an estimate is the bill of quantities, which is the only information about the potential project defined in the tender documentation, and databases of completed projects on the basis of which it is necessary to complete the preliminary estimation of cost and duration.

2 Artificial neural networks

The beginning of the development of neuro-computing is linked with the article by McCulloch and Pitts [4]: "A logical calculus of the ideas immanent in nervous activity". Taking into account that the development of artificial neural networks (ANN) and their wider application are quite recent, it is clear that there is still no single definition that explains them fully. One of the definitions offered, from an engineering point of view, in current literature is: "A computational mechanism able to acquire, represent and compute mapping from one multivariate space of information to another, given a set of data representing that mapping [5]."

ANNs are an attempt to imitate the work of biological neural networks with adequate mathematical models (structure, function and method of processing information), i.e. they have the ability to learn, memorize, recognize, and to generalize the rules.

The basic processor element of an ANN is a *neuron*. One of the most commonly used mathematical models of neurons is the McCulloch-Pitts model, the so-called M-P neuron (see Fig. 1).

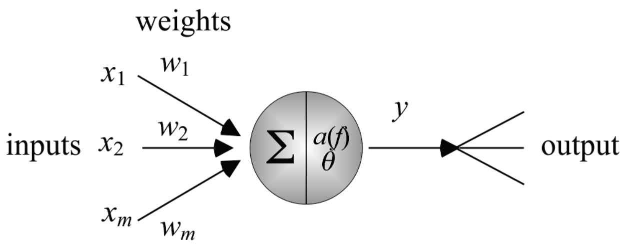


Figure 1 McCulloch-Pitts model of neuron

From the picture, an analogy can be seen of the *biological neuron-mathematical model of neurons*. The input data (x_1, x_2,.. x_m) with weight coefficient (w_1, w_2,... w_m) represents dendrites. In the body of a neuron summarizing occurs, i.e. processing, of a signal on the basis of which the neuron is activated or not activated. If there is activation, the signal is transmitted through the output (axon) to the next neuron with which the observed neuron is connected.

The main tasks associated with a processing unit are to receive input from its neighbors providing incoming activations, compute an output, and send that output to its neighbors receiving that output. Neurons in an ANN can be classified into one of three groups: input neurons, hidden neurons and output neurons [6].

The ANN mathematical model consists of three basic parts, namely: *the mathematical model of the neuron itself*, *the architecture of the network* (models of the synaptic connections and the structure of the neurons in the network) and *the rules for training the network*.

The first scientific article related to the application of neural networks in the construction industry was published by Adeli and Yeh in 1989 [7]. The application of ANN in the construction industry is becoming increasingly common with the development of software in which the sphere of their application in the construction industry is very broad, from structural engineering to construction engineering. As far as construction engineering is concerned, ANNs are often used in the planning and management of construction projects, estimation of project costs and in the planning and allocation of resources and similar.

Kim et al. [8] by comparing the multiple regression model (MRM), neural network model (NNM) and case-based reasoning model, (CBR) came to the conclusion that ANNs provide the most accurate results regarding cost estimates.

3 Methods

Forming an ANN model passes through three phases: the network modelling phase, the network training phase and the phase of evaluating the performance of the ANN [9]. These three phases of the formation of ANNs are very important, but for the quality functioning and applicability of ANN, the quality of available *data bases* for training is of great significance.

The ANN modelling phase, i.e. defining the network architecture, involves defining a series of parameters such as the number of input parameters, the number of layers and the number of neurons in them, the amount of output data, the selection of activation functions of the neuron, as well as the type of training function, and whether the network is oriented forwards or backwards.

After defining the architeture of the ANN the *training phase of the ANN begins.* Training the ANN is based on either training the structure of the network or training the weight (so-called parametric training). A training algorithm is also important. There are three training algorithms: supervised training, reinforcement training and unsupervised training.

The ANN testing phase involves comparison of the output values from the ANN, based on the data set for testing, with the expected values. By comparing these quantities, it is possible to check whether the ANN gives satisfactory output or whether it is necessary to make adjustments to the structure of the network.

3.1 The formation and preparation of a database

The main precondition for the application of an ANN is the establishment of an adequate database. Within the framework of the research shown in this paper, data was gathered on completed projects in the construction of urban roads and associated landscaping. The data collected was based on work carried out by the same contractor, whose use of the same machinery and human resources was generally constant. All of the work carried out was completed using similar methods, and subcontractors were not used for any of the projects. It is important to mention that all of the completed projects were carried out in the same region under the same climatic conditions, since they greatly influence the time taken for completion of a project, and therefore, the total cost of its implementation [10].

The database established consists of 130 successfully completed projects related to the construction of new and the rehabilitation of existing urban roads, and their associated landscaping works. Because of the most important part of the tender documentation, upon which the preliminary estimate of time and cost is based, *the bill of quantities,* works were grouped in the following way:

- preparatory works (PW)
- earthworks (EW)
- road construction and landscaping (RCL)
- drainage works (DW)
- works on traffic signalization (WTS).

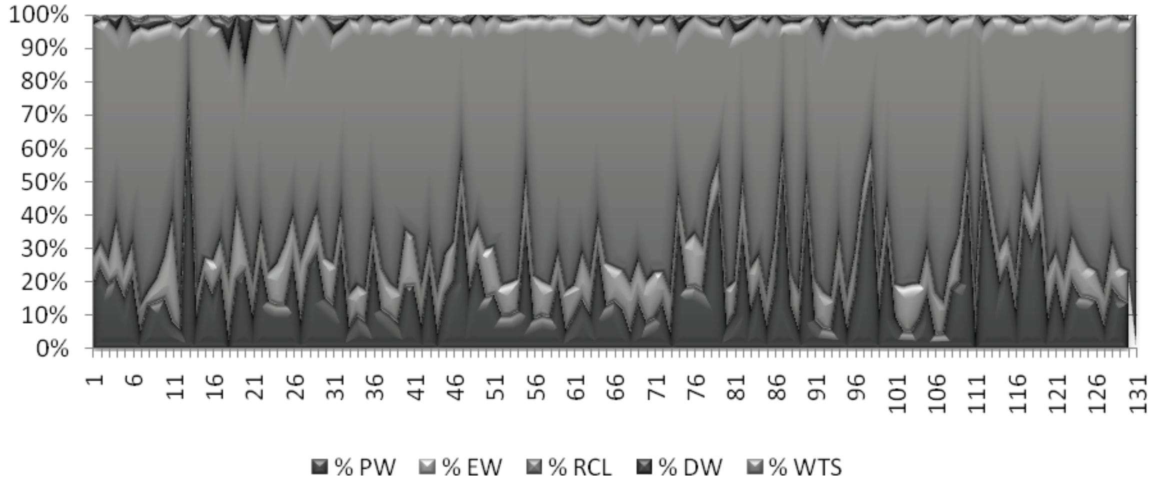


Figure 2 Diagram of percentage share of total cost by type of work

In order to prepare data for processing using ANN, an analysis of the most significant works in terms of cost within the framework of each completed project was carried out (see Fig. 2).

It can be clearly seen from the diagram that the most significant costs are road construction and landscaping. Guided by this fact, the mentioned works are given the most importance during the database analysis. Considering that the starting point of the preliminary estimate is the bill of quantities, it is necessary for road construction and landscaping to be connected with it. In this case it is based on the large quantities of the most common basic materials, such as:

- the quantity of crushed stone (i_1), m^3
- the quantity of concrete curbs (i_2), m
- the quantity of bituminous wearing course (i_3), t
- the quantity of asphalt concrete (i_4), t
- the quantity of pressed concrete slabs (i_5), m^2.

Of course, for it to be a comprehensive analysis, other works have not been neglected: preparatory works (i_6), earthworks (i_7), drainage works (i_8) works on traffic signalization (i_9), whose involvement is taken into account on the basis of their presence and complexity in the total volume of works, which is determined by expert evaluation on the basis of earlier completed works (see Tab. 1).

Table 1 Work amount levels

Level 0	Works are not present
Level 1	Regular amount of works
Level 2	Slightly increased amount of works
Level 3	Medium increased amount of works
Level 4	Considerably increased amount of works

Thus, the basic materials mentioned for road construction and landscaping (quantitative data), i.e. their amounts, and work done which is defined in levels (qualitative) are the input data for an ANN.

Since the subject of the research is the preliminary estimation of cost and duration of implementing a project, it is clear that the output data from an ANN is:

- total realization cost of the project (€) and
- total time required for the project completion (calendar days).

Taking into account that there is a clear distinction in the order of magnitude of the data from 0 do 10^5 (see Tab. 2) it is necessary to prepare the data in order for it all to be analyzed equally, i.e., it is necessary to carry out normalization of the data. Normalization of the data leads to an increase in performance of the trained ANN. [9,11] Based on the above, normalization of the whole database was carried out i.e. the input and output data both in the training set and in the testing set for the ANN.

Normalization of the data was performed using "Z-Score" transformation in the distribution where the mean is (μ) 0, and the standard deviation (σ) 1 using the following expression [12], Eq. (1):

$$S_{ij} = \frac{X_{ij} - \mu_i}{\sigma_i} \tag{1}$$

where:
S_{ij} – is the normalized data value
X_{ij} – is the actual data value
μ_i – is the mean distribution (data set for training)
σ_i – is the standard deviation of the distribution (data set for training)
i – is the input ($i = i_1, i_2, \dots, i_9$) or output ($i = o_1, o_2$) data

j – is the number of combinations (j = 1, 2,……, n); n is the number of data sets.

The shown normalized data (see Tab. 2) is the basis for training the ANN. Of course, given that training of the ANN is carried out based on normalized data, the output from the ANN is also normalized. It is necessary to transform the output in order to obtain real values comparable with the expected values from the data sets for testing the ANN on the basis of which error is determined [12]. The transformation is performed using the following expression, Eq. (2):

$$X^{\text{real}}_{ij} = S^{NN}_{ij} \cdot \sigma_i + \mu_i, \tag{2}$$

Table 2 Intervals of real and normalized input and output data

Input data	No.	Measure unit	min (real)	max (real)	min (normalized)	max (normalized)
The quantity of crushed stone	i_1	m^3	0,00	7 130,70	−0,8291	4,7340
The quantity of concrete curbs	i_2	m	28,00	12 470,00	−0,6870	5,2250
The quantity of bituminous wearing course	i_3	t	0,00	1 890,00	−0,6800	4,9700
The quantity of asphalt concrete	i_4	t	0,00	1 171,35	−0,8697	5,0652
The quantity of pressed concrete slabs	i_5	m^2	94,50	18 167,50	−0,7455	5,6620
Preparatory works	i_6	level	1	4	−1,6310	2,2767
Earthworks	i_7	level	1	4	−1,0818	2,9639
Drainage works	i_8	level	0	4	−1,9292	1,2554
Works on traffic signalization	i_9	level	0	4	−1,3389	1,7000
Output data		**Measure unit**	**min (real)**	**max (real)**	**min (normalized)**	**max (normalized)**
Total cost of project	o_1	€	9 211,46	506 762,94	−1,1399	2,8844
Total time required for project	o_2	calendar days	8,00	62,00	−1,8616	2,3948

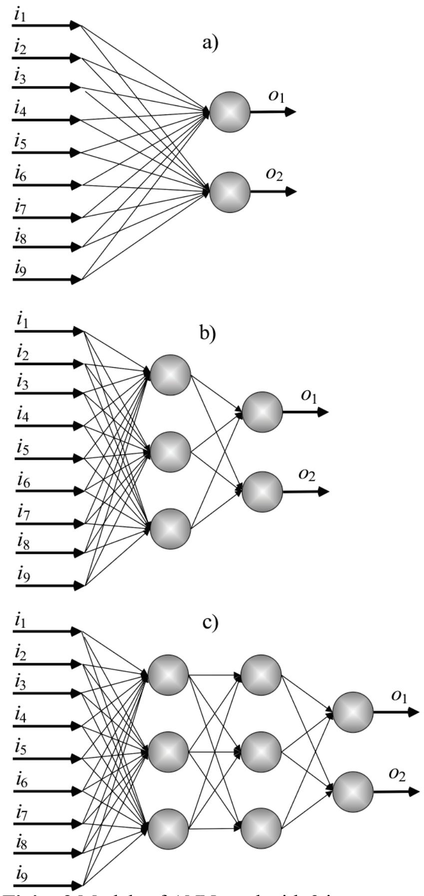
where:
S^{NN}_{ij} – is the normalized data value obtained as output from the ANN
X^{real}_{ij} – is the real data value obtained on the basis of S^{NN}_{ij}
μ_i – is the mean distribution (data set for training)
σ_i – is the standard deviation of the distribution (data set for training)
i – is the output data ($i = o_1, o_2$)
j – is the number of combinations (j = 1, 2,..., m); m – is the number of data sets for testing.

Analysis of the database was divided into two parts:
- the first part made up of 115 data sets for training ANN and
- the second part made up of 15 data sets for testing ANN.

When dividing the database into two parts, one for training and the other for testing the ANN, attention is paid to all of the input and output data from the set for testing being within the range of min and max data values for training, i.e., that the min and max values of all data are found within the data set for training ANN [11].

3.2 Modelling the ANN

In the phase of defining the ANN model, the required amount of input and output data is defined first. The number of input parameters determines the spatial dimensions of the network and the number of output parameters determines the number of solution surfaces generated by the network [13, 14]. The amount of input data is defined by the formation of a database based on the analysis carried out as to the significance of individual data, while the amount of output data is defined by the amount of information required as the end result of the application of a neural network.



Figire 3 Models of ANN used with 9 inputs: (a) 1L, (b) 2L-3N, (c)3L-3N1-2

The number of neurons in layers drastically affects the response of the neural network. Neurons in hidden layers not only process the data but also affect the level of freedom of the neural network, which is of great significance to the accuracy of the modeled network [15].

Both in terms of defining the number of layers and the number of neurons in them, there are no fixed rules, they are most often determined by iterative means [16, 17].

As part of the research, three models of neural networks were formed: a network with one layer (1L), a network with two layers with three neurons in the first layer (2L-3N1) and a network with three neurons in both the first and the second layers (3L-3N1-2) (see Fig. 3).

In addition to defining the number of layers and the number of neurons in them, the transfer functions of neurons are also defined, which define how data is transferred from neuron to neuron.

For the ANN models shown (see Fig. 3) as a transfer function for all neurons the hyperbolic tangent sigmoid transfer function was used, except for the neurons in the output layers of the networks with two or three layers for which the linear transfer function was used.

3.3 Training the ANN

ANN training within this study was carried out by applying an algorithm with supervision and backpropogation of errors taking into account that it has the widest application, particularly when it comes to cost prediction [2, 8, 17, 18].

ANN modelling was done using the MATLAB R2007b software package. In the research presented in this paper different training functions were used (see Tab. 3) in order to see their effect on the ANN modelling.

Table 3 Used training functions

TRAINING FUNCTIONS	
traingda	Gradient descent with adaptive lr backpropagation.
trainlm	Levenberg-Marquardt backpropagation.
trainbfg	BFGS quasi-Newton backpropagation.
trainbr	Bayesian regularization.
traincgb	Powell-Beale conjugate gradient backpropagation

The three defined ANN models (1L, 2L-3N1 i 3L-3N1-2) were trained using all five of the training functions given, so that for the purposes of this study a total of fifteen ANNs were trained. Training was conducted on 115 sets of input and output data.

When training the ANN, as a criterion for stopping it, a limit of 400 epochs was set (the number of epochs is understood as the number of times the data passes through training with the ANN) [16].

3.4 Testing the ANN

Testing the ANN, i.e. evaluation of its performance, can be done on the basis of different criteria. The most commonly used criteria for statistical evaluation are the mean, standard deviation and cofficient of variation [8]. However, in this research the performance of the ANN was evaluated on the basis of MAPE (mean absolute percent error) using the following expression [19], Eq. (3):

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{\left|actual_i - predicted_i\right|}{predicted_i}\cdot 100\,\%, \tag{3}$$

where n is the number of data sets for testing.

Using MAPE, the mean percentage deviation of the output values from the ANN is shown in relation to the real (collected) data. It is also possible to use MAER (mean absolute error rate) which indicates the deviation from the mean percentage deviation of the real data compared to the estimated values [8, 20].

As already mentioned in the research, ANN models with different training functions were formed. After the completed training, testing was carried out, and the results are shown in Tab. 4. Testing was conducted on 15 sets of input and output data which were not taken into account when the network was being trained. Besides testing all the neural networks on the basis of MAPE, their stability was also tested.

The stability of the ANN was tested by comparing the MAPE for five consecutive iterations of prediction for each network. If MAPE differs from the iterations of prediction the network is considered unstable, i.e. it will not always carry out a prediction with the same accuracy.

It can be clearly seen from the Tab. 4 that the best results are given by the ANN without hidden layers, followed by the network with only one layer, and the training function *trainbr* (Bayesian regularization), while the remaining ANNs with one layer give the same or very similar results, with the exception of the ANN with the training function *traingda* which proved itself to be unstable. The ANN with two (2L-3N1) and three (3L-3N1-2) layers as well as having a greater MAPE proved themselves to be unstable.

For the chosen ANN (1L-tarinbr), the following graph (see Fig 4.) shows the deviation of PE (percentage error), Eq. (4), obtained on the basis of the data set for testing the network.

$$PE = \frac{actual_i - predicted_i}{predicted_i}\cdot 100\,\%. \tag{4}$$

It can be clearly seen from the graph (see Fig. 4) that the maximum deviation of the output values from the ANN, in comparison with the expected values, was 12,71 % for cost and 10,41 % for the period of construction.

Too many input and output parameters will drastically slow down the learning process and too few sets of training data can provide insufficient information about localised features and cause the network to fail to generalise, and the network response to unseen data will be poor. It is therefore essential to optimise the number of input and output parameters as much as possible [16].

Guided by the previous statement, optimization of the input data was carried out. The output data remained unchanged, given that the subject of the research is using ANN with the same parameters to make predictions of the cost and duration of realizing projects. Optimization of the input data was performed using sensitivity analysis (for the neural network 1L-trainbr) in order for the input data to influence the efficiency of the ANN (see Fig. 5). Sensitivity analysis provides vital insights to the usefulness of individual input variables. Through sensitivity analysis, variables that do not have significant effect can be taken out of the neural network model and key variables can be identified [21].

Table 4 MAPE of neural networks with nine inputs

Training functions	Output	NETWORK 9 inputs and 2 outputs		
		1L	2L-3N1	3L-3N1-2
		MAPE		
traingda	Total costs	Unstable / %	unstable	unstable
	Total time required			
trainlm	Total costs	7,38	unstable	unstable
	Total time required	3,97		
trainbfg	Total costs	7,38	unstable	unstable
	Total time required	3,97		
trainbr	Total costs	**6,52**	unstable	unstable
	Total time required	**3,85**		
traincgb	Total costs	7,39	unstable	unstable
	Total time required	3,97		

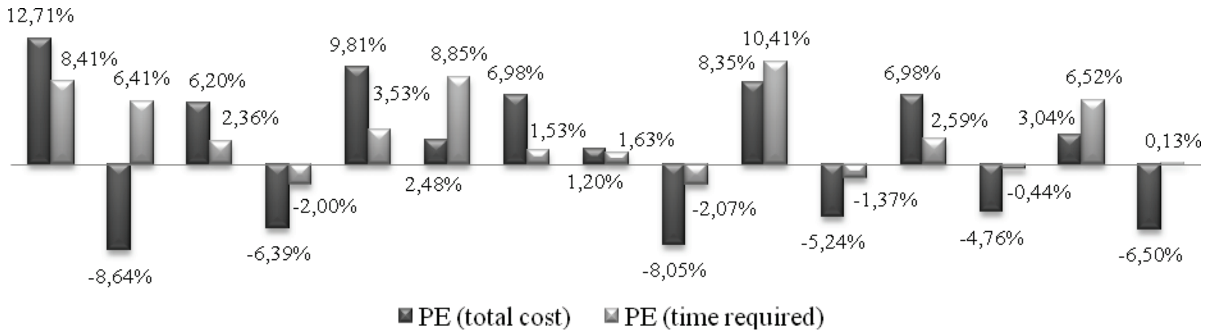


Figure 4 The Graphic PE of each individual piece of data for testing 1L-trainbr (network with nine inputs)

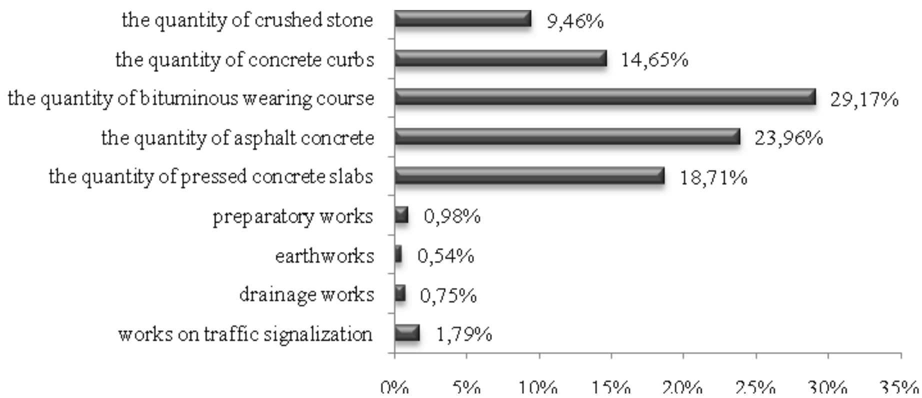


Figure 5 Sensitivity analysis for the ANN 1L-trainbr (network with nine inputs)

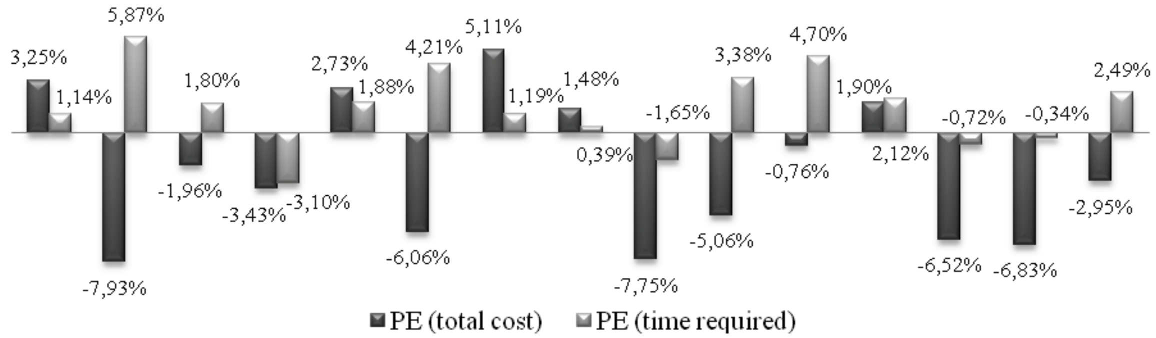


Figure 6 A PE graph of individual data for testing 1L-tarinbr (network with five inputs)

Using sensitivity analysis it was concluded that the following input data: signalization works, drainage works, earthworks and preparatory works have a total involvement of only 4,06 % which means in practice that they do not have a great influence on the ANN and that they can be ignored. Such a conclusion can be made on the basis of defining the most important activities in terms of cost (see Fig. 2), but no confirmation can be made with any certainty that they do not influence the time necessary for carrying out the work, which is now confirmed by the sensitivity analysis.

After eliminating the "less" important input data, formation, training and testing of the ANN were carried out again, but instead of using nine inputs, only five were used, i.e. five sets of input data (i_1, i_2, i_3, i_4, i_5,), which apply only to the quantity of basic materials used for road construction and landscaping.

An analysis was carried out identical to the one for the previous input data. The best results, i.e. those with the lowest mean absolute percent error (MAPE), were achieved using the ANN with one layer and with the training function *trainbr* ($MAPE_{\text{total cost}}$ = 4,25 %; $MAPE_{\text{construction period}}$ = 2,33 %). In Fig. 6 is a PE graph for the data set for testing the ANN (network with five inputs) obtained on the basis of PE (percentage error).

It can be clearly seen from the graph (see Fig. 6) that the maximum deviation of the output values from the ANN 1L-tarinbr (network with five inputs), in comparison with the expected value, is 7,93 % for cost and 5,87 % for the construction period. The ANN 1L-tarinbr with five data inputs was further analyzed and during the processes of testing and training it gave the same output results for five consecutive iterations, so it can be regarded as stable.

4 Conclusion and further study

The application of ANN for the simultaneous conceptual estimation of works to be carried out and their duration on the basis of the analysis conducted and the results obtained proved to be acceptable. The maximum deviation of the output data in comparison with the real values is less than ±8 % which is acceptable for the conceptual estimation of the real cost and duration of works. This approach significantly increases the quality of decisions made regarding the involvement in potential projects and it reduces the risk of going over the budget and time envisaged for construction.

Regarding the data used for analyzing the ANN, there are a number of limitations. Since the database was formed on data from the same contractor, there is no possibility of using the resulting ANN for the prediction of the cost and duration of works carried out by other contractors, or for works carried out in regions where there is a significant difference in the climatic conditions. However, this approach to predicting the cost and duration of works has proved to be satisfactory, as far as a conceptual estimate is concerned, of course inasmuch as the potential user has a database of works already completed (real cost and time for completion of the works). In addition to the limitations mentioned, it is important to note the limitations related to the range of data within the database. If a project appears that for any of its parameters (input or output) goes beyond the range of the database analyzed, the ANN will not give adequate results. Thus, the process of using ANN requires constant training of the network, i.e. updating it with new information in order for the ANN to become more comprehensive.

The direction for further research can be seen in the formation of an ANN for the preliminary estimate of cost and duration of works which would not have any limitations, i.e. it would be more comprehensive regarding the possibilities for its wider use regardless of who the contractor is or what climatic conditions they are working under. The authors of this study consider that these kinds of neural networks require the formation of adequate databases, which would result in more comprehensive collection of data. The collection of data would have to include a larger number of contracting companies, and for an even wider application, works carried out in different climatic zones. In addition to this, a different approach to collecting and preparing information is necessary, where alongside data about the work itself, it would be necessary to include parameters which characterize both the contractors and the locations in which they are working. Given that this approach requires a large amount of input data, it is essential for the database to be adequate, i.e. to collect a significantly higher number of input and output data sets in comparison with the database formed for the purposes of this research.

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5 References

[1] Ivković, B.; Popović, Z. Project Management in Construction. 3rd ed. Gradjevinska knjiga, Belgrade, 2005. (in Serbian)
[2] Al, T. H.; Alex, A. P.; Tantash, M. Preliminary cost estimation of highway construction using neural networks. // Cost Engineering. 41, 3(1999), pp. 19-24.
[3] Stewart, R. D.; Wyskida, R. M.; Johannes, J.D. Cost estimator's reference manual. 2nd ed. USA: John Wiley & Sons, Inc., 1995.
[4] McCulloch, W. S.; Pitts W. A logical calculus of the ideas immanent in nervous activity. // Bulletin of Mathematical Biophysics. 5(1943), pp. 115-133.
[5] Garret, J.H. Where and why artificial neural networks are applicable in civil engineering. // ASCE Journal of Computing in Civil Engineering (special issue), 8, 2(1994), pp. 129-130.
[6] Kartam, N.; Flood I. Artificial neural networks for civil engineers: fundamentals and applications. American Society of Civil Engineers, USA, 1997.
[7] Adeli. H. Neural networks in civil engineering: 1989 – 2000. // Computer-Aided Civil and Infrastructure Engineering. 16 (2001), pp. 126-142.
[8] Kim, G. H.; An, S. H.; Kang, K. I. Comparison of construction cost estimating models based on regression analysis, neural network, and case-based reasoning. // Building and Environment. 39(2004), pp. 1235-1242.
[9] Günaydin, H. M.; Doğan, S. Z. A neural network approach for early cost estimation of structural systems of buildings. // International Journal of Project Management. 22(2004), pp. 595-602.
[10] Peško, I.; Ćirović G.; Mučenski, V.; Tepić, Ž.; Dražić, J.; Trivunić, M. Analysis and preparation of data in neural networks calculation stage for the purpose of creating business proposals. // Organization, Technology and Management in Construction, Book of Abstracts / editors Anita Cerić, Maja-Marija Nahod, Mladen Radujković, Mladen Vukomanović. Šibenik: Faculty of Civil Engineering University of Zagreb, Croatian Association for Construction Management, 2011. pp. 57.

[11] Setyawati, B. R.; Creese, R. C.; Sahirman, S. Neural network for cost estimation (Part 2). // AACE International Transactions. EST.14(2003), pp. 14.1-14.10.
[12] Wu, J. S.; Han, J.; Annambhotla, S.; Bryant, S. Artificial neural networks for forecasting watershed runoff and stream flows. // ASCE, Journal of Hydrologic Engineering. May/June (2005), pp. 216-222.
[13] Flood, I.; Kartam, N. Neural network in civil engineering I. // ASCE, Journal of Computing in Civil Engineering. 8, 2(1994), pp. 131-162.
[14] Flood, I.; Kartam, N. Neural network in civil engineering II. // ASCE, Journal of Computing in Civil Engineering. 8, 2(1994), pp. 131-162.
[15] Adya, M.; Collopy, F. How effective are neural networks at forecasting and predictions? // Journal of Forecasting. 17, 5/6(1998), pp. 481-495.
[16] Rafiq, M. Y.; Bugmann, G.; Easterbrook, D. J. Neural network design for engineering applications. // Computers and Structures. 79(2001), pp. 1541-1552.
[17] Setyawati, B. R.; Sahirman, S.; Creese, R. C. Neural network for cost estimation. // AACE International Transactions. EST.13(2002), pp. 13.1-13.9.
[18] Ćosić, P.; Lisjak D.; Antolić D. Regression analysis and neural networks as methods for production time estimation. // Tehnički vjesnik-Technical Gazette. 18, 4(2011), pp. 479-484.
[19] Sonmez, R. Conceptual cost estimation of building projects with regression analysis and neural networks. // Canadian Journal of Civil Engineering, 31(2004), pp. 677-683.
[20] Kim, G. H.; Yoon, J. E.; An, S. H.; Cho, H. H.; Kang, K. I. Neural network model incorporating a genetic algorithm in estimating construction cost. // Building and Environment, 39(2004), pp. 1333-1340.
[21] Tatari, O.; Kucukvar, M. Cost premium prediction of certified green buildings: A neural network approach. // Building and Environment, 46(2011), pp. 1081-1086.

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