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Use of artificial intelligence for estimating cost of integral bridges

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Subject review

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Estimation of costs is important in every phase of realisation of construction projects. However, the influence of cost estimation is the highest in early phases as it is then that the decision about accepting the job or withdrawing from the project is made. The quantity of data available in initial phases of the project is smaller compared to subsequent phases, which affects accuracy of cost estimation in such early phases. A research making use of artificial intelligence to estimate construction costs of integral road bridges is presented in the paper. The estimation model is prepared by means of neural networks. The best neural network model has proven to be highly accurate in the estimation of costs based on the mean absolute error, which amounts to 13.40 %.

Key words:

integral road bridges, cost estimation, artificial intelligence, neural networks

Pregledni rad

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Procjena troškova za integralne mostove primjenom umjetne inteligencije

Procjena troškova u svakoj fazi realizacije projekata u građevinarstvu je važna. Ipak, utjecaj procjene je najveći u ranim fazama jer se tada opredjeljuje o prihvaćanju posla ili odustajanju. Rane faze realizacije projekata oskudijevaju s količinom potrebnih podataka u odnosu na sve sljedeće faze što utječe na preciznost procjene troškova u ranim fazama. U radu je prikazano istraživanje u kojem se upotrebom umjetne inteligencije izvršila procjena troškova pri izgradnji integralnih cestovnih mostova. Model za procjenu izrađen je uz pomoć neuronskih mreža. Najbolji model neuronskih mreža pokazao je visoku točnost pri procjeni troškova na osnovi srednje apsolutne pogreške, koja iznosi 13,40 %.

Ključne riječi:

integralni cestovni mostovi, procjena troškova, umjetna inteligencija, neuronske mreže

Übersichtsarbeit

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Kostenschätzung für integrale Brücken unter Verwendung künstlicher Intelligenz

Es ist wichtig, die Kosten in jeder Phase der Projektumsetzung im Bauwesen abzuschätzen. Die Auswirkungen der Schätzung sind jedoch in den frühen Phasen am größten, da dann entschieden wird, den Auftrag anzunehmen oder davon abzusehen. In den frühen Phasen der Projektumsetzung fehlt die für alle nachfolgenden Phasen erforderliche Datenmenge, was sich auf die Genauigkeit der Kostenschätzungen in den frühen Phasen auswirkt. Die Arbeit präsentiert eine Studie, bei der mithilfe künstlicher Intelligenz die Kosten für den Bau integraler Straßenbrücken abgeschätzt wurden. Das Schätzmodell wurde unter Verwendung neuronaler Netze entwickelt. Das beste neuronale Netzwerkmodell zeigte eine hohe Genauigkeit bei der Schätzung der Kosten basierend auf dem mittleren absoluten Fehler von 13,40 %.

Schlüsselwörter:

Integrale Straßenbrücken, Kostenschätzung, künstliche Intelligenz, neuronale Netze

1. Introduction

Civil engineering is a complex sphere of industrial activity. The complexity of civil engineering can be seen in the uniqueness of each project. In addition, this unique nature of civil engineering can also be seen in a considerable number of participants that take part in the realisation of projects. Participants in the realisation of construction projects are: client, consultant, designer, expert supervision team, contractor, and various interested parties. The initiative for the start of the project realisation process is made by the client, which is why this entity has the leading role in this process. Contractor also assumes a significant role in the realisation of projects and so, by importance, the contractor comes right after the client. The contractor is the direct implementer of construction work. The client is responsible for selection of the contractor. The client selects the contractor based on specific criteria. These criteria are often hard to fulfill and, in general, they involve realisation of the project at the lowest possible cost, in the shortest possible time span, and to the highest possible quality standards.

The estimation of cost is made separately by the client and the contractor. The ensuing project evaluation steps are dependent on this initial estimation of cost. Sometimes the estimation of costs results in the withdrawal from the project.

The quality and reliability of estimation, as related to the desired level of accuracy, depend on a number of factors. Some of these factors are: availability, quality and level of detail of technical documents, the way in which estimation is made, and competence of experts that conduct the estimation procedure. The availability of necessary data increases with the advancement of the project, when the accuracy of the estimation also becomes higher. The reliability of cost estimation according to Barnes (1974) is shown in Figure 1 [1].

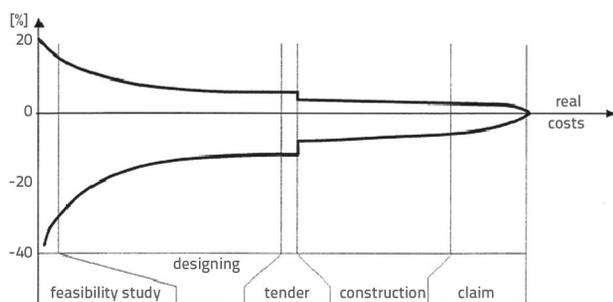


Figure 1. Reliability of cost estimation according to Barnes [1]

In most cases, the basic and often the only criterion for the realisation of the project is the price offered by the contractor. The contractor whose bid price is the lowest is entrusted with realisation of the project. In this contractor selection method, the question can be put about whether the company selected by the client will complete the project in an expected, or at least satisfactory, manner (with regard to quality and time).

In this research, the cost of realisation of construction projects is estimated based on the values taken from cost estimates contained in the design documentation. These cost estimates serve as basis for the award of construction contracts. The

contractor usually prepares two estimates, i.e. the conceptual one (rough estimate) and the preliminary estimate (a more detailed estimation) [2].

The conceptual estimate is used to determine whether it is justified to continue with subsequent phases of realisation of the project. The preliminary estimate results in a detailed bid in which the analysis of cost structure is given. All estimates are based on available documentation provided by the client (bidding documents). As the number of input data is the smallest in the initial phase, the conceptual estimate is just a rough estimation. This brings us to the question of the satisfactory or required accuracy of estimates. According to some research results, the accuracy of estimates made in early phases of projects range between $\pm 25\%$ and $\pm 50\%$ [3-5] or between 13% and 31% [6]. Some other studies show that the accuracy of estimates made in early phases of project realisation range between $\pm 15\%$ and $\pm 20\%$ [7]. The accuracy level of $\pm 15\%$ was adopted for the purposes of the present research.

2. Use of artificial neural networks in civil engineering

The use of one of the artificial intelligence techniques, i.e. neural network technique, is quite widespread in civil engineering as these networks can be used in all phases of project realisation. A paper on the use of neural networks in this field was published in journal *Microcomputers in Civil Engineering* in 1989 [8]. Supported by development of computer programs neural networks are now increasingly used in civil engineering.

Various estimations can be made by means of neural networks. One of them is the estimation of the cost of construction work. This technique is often used for such purposes as demonstrated by a considerable number of papers written on this topic (construction cost estimate for residential and/or residential-office buildings [9], estimate of bridge repair costs [10], construction cost estimate for hydropower plants [11], construction cost estimate for water supply and drainage networks [12], etc.). Results of the use of neural networks in the field of civil engineering are presented in a considerable number of papers.

The authors of the paper used neural networks to prepare a model for parametric estimation of motorway construction costs [13]. The parameters that influence the change in overall road construction costs were determined through survey of a number of project managers that have used neural networks [14]. The estimation of motorway construction costs based on neural networks has been presented in a number of studies. Thus for example in [5] the author's focus was on development of accurate prediction models in the sphere of motorway construction in developed countries in initial project phases. In this research, the author used the so called ROCKS database (database prepared by the World Bank: Road Costs Knowledge System). This database contains road construction data from 65 countries. Out of these 65 countries, the greatest number of projects were realised in Poland and Thailand, and so the model analysis and shaping was conducted based on the data obtained in these countries. As many as 315 projects were realised in Poland,

out of which 38 were selected for the analysis of the first model. The works that are significant for costs were taken as input variables. 123 projects were conducted on Thailand, out of which 42 were selected for the analysis of the second model. Unlike the first model, in this model the number of input variables was reduced to the total of 3. In both cases, the database set was divided into three parts, namely: learning data 60 %, validation data 20 %, and testing data (20 %). The model accuracy evaluation was made using the mean magnitude of relative error (MMRE). Sodikov also estimated construction costs by means of a multiple regression model. By comparing the results obtained using these two methods, he concluded that neural network models were more accurate in both cases. For the projects conducted in Poland, the accuracy was 24 %, and for those conducted in Thailand the accuracy was 26 %. The author concluded that neural networks can successfully be used for predicting costs in early phases of projects.

Several authors have also considered the issue of cost estimation in early phases of projects. A model for estimating cost increase risk in building engineering was developed using the neural networks model [15].

An overview of motorway construction cost estimations based on neural networks was also given by other authors in [16].

This technique was also used to estimate motorway construction costs in Louisiana. The model describes total construction costs as related to the motorway construction cost index [17].

Relevant literature also includes a paper in which construction costs are estimated for 4- to 8-storey residential and office-residential buildings situated in Turkey. The prediction accuracy of this model was 93 % [18].

Bridge repair costs were also analysed by some authors. The aim of their research was to describe the damage observed on bridges after Hurricane Katrina and to present general observation about the repair costs of these bridges. Neural networks were used in the estimation of repair costs [19].

Neural networks were also used in order to estimate the cost of construction of a wastewater treatment plant in Oklahoma [20].

Artificial neural networks were used to estimate the value of investment in the repair of railway lines. The model was prepared to improve the efficiency and effectiveness when making decisions about investment in rail infrastructure projects. It was concluded that the model can be applied for rough and rapid estimation of investment value of railway repairs, and that its accuracy ranges from 80 to 85 % if all input parameters are not known [21].

A study showing discrepancy between real costs and estimated costs was made on the data sample of 258 transport related projects. It was established during the study that not only were nine out of ten project underestimated but that real costs were on an average 28 percent higher compared to initial estimates. However, the most interesting conclusion was that the current percentage of underestimated costs is no different than the percentage registered for the past seventy years [22].

A model for predicting total construction costs, based on the linear regression technique, is also shown in literature. A database from 300 projects was used in the preparation of the model. The model was evaluated using the neural networks method. The results have

shown that the main advantage of neural networks is their capability of modelling the nonlinearity of data. The model has revealed that the accuracy according to MAPE amounts to 16.5 % [23].

The estimation of building construction costs at early stages of construction projects was also studied. The database used for defining the model contains the data from 71 projects. The following data were adopted as input variables: foundation method, ground floor area, area of a typical storey, number of storeys, number of elevators, number of rooms, and number of columns. The model was prepared by means of neural networks using a multilayer perceptron. This resulted in the model whose accuracy according to MAE amounts to 16.6 % [24].

3. Materials and methods

Appropriate data were collected and analysed for the purposes of this research. After that, the data for forming the model were prepared. The final model for the estimation of construction costs was then defined.

The data were obtained from detailed design documents for integral road bridges built in various part of Montenegro, Bosnia and Herzegovina and Serbia. The term "integral bridges" is the modern name for concrete and composite frame bridges without expansion joints and bearings [25]. Here it should be noted that there are several definitions of integral bridges. In effect, in literature, integral bridges are defined as single span frames without expansion joints and bearings. However, according to some other definitions, integral bridges are also the bridges with continuous frames without expansion joints and bearings, but only above central piers. The projects from which the data used in this research were collected are either completed or are at the final stage of realisation. The bill of quantities and cost estimate form an integral part of technical documents that are prepared in the scope of detailed design for bridges. All data used in this research were collected from these documents. These bridges vary from 11.5 to 28 meters in span, and the number of span ranges from one to eighteen. Bridge lengths without wing walls range from 11.5 to 784.4 meters, and piers vary from 2.8 to 65 m in height. These projects were realised in the period from 2010 to 2016.

113 structures were analysed in the scope of this research: 48 bridges from Montenegro, 41 bridges from Bosnia and Herzegovina, and 24 bridges from Serbia. As the bridges were built in three different countries, the design documentation also differed by format and content. That is why the analysis and data preparation phases proved to be quite complex. In order to achieve a good level of uniformity, only the same types of works were taken from the bills of quantities and cost estimates. Thus the bills of quantities and cost estimates considered in the research covered the same types of works. In these bills of quantities and cost estimates the types of works are divided as follows: preliminary works, earthwork, concrete work, reinforcement steel bending works, prestressing work, insulation works, asphalt works, and finishing works.

The proportion of individual types of works in the total price was analysed. The analysis resulted in the determination of the works

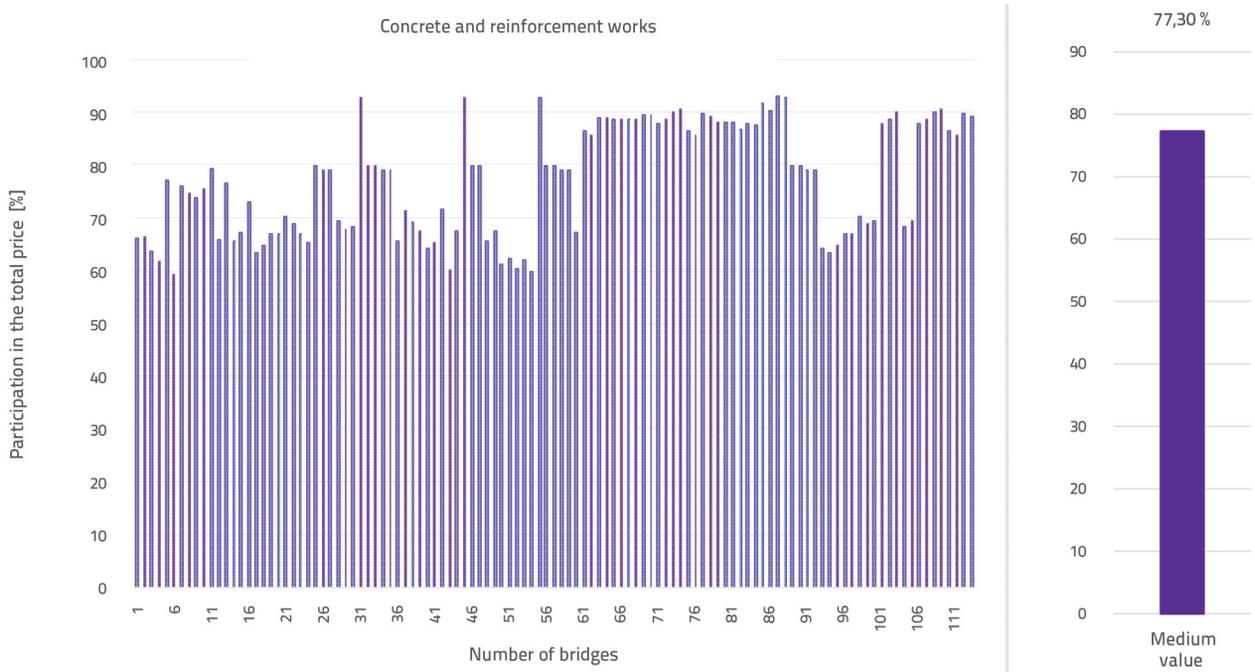


Figure 2. Percentage of concrete and steel bending works in the total price

that are most represented in the total price. These are the concrete and steel bending works, and their proportion in the total price of construction work is 77.305, as shown in Figure 1. The percentage of these works in overall works is 25 %. By approximating the above percentage values, it can be concluded that 20 % of work items participated with as much as 80 % in the total price.

The participation of concrete and steel bending works in the total price varies from 70 to 90 percent on 69 projects, i.e. on 61.06 % of the total number of analysed projects. This fact shows that on 61.06 % of the projects the proportion of the total price varies by ± 10 % compared to 80 %. Taking this into account, it can be said that steel bending and concrete works are, as to their cost, significant work items according to Pareto distribution.

The most traditional way of estimating costs is by applying unit price to the previously calculated quantities of works [2]. The bill of quantities and cost estimate are an integral part of the design documentation that is provided by the client, and that is always at the contractor's disposal during preparation of the bid. However, in early phases of the realisation of projects, when the quantity of input data is very limited, the bill of quantities and cost estimate can not be prepared. This is why other cost estimation methods are used. These methods are aimed at making the estimation at the highest possible level of accuracy, within a short time period, and based on data that are available at the time of estimation.

Design properties of bridges to be used as input data for estimation were defined based on identification of cost-significant types of work. In this respect, characteristics that directly influence the cost-significant types of works were selected. These characteristics are: bridge length, bridge width, bridge pier height, and bridge span. All these bridge characteristics were taken from detailed design documents of the bridges considered in this research. As a considerable number of different bridges (as to their pier height)

were analysed, it was necessary to unify these data and reduce them to a single value for each bridge. For that reason, the height of piers, as an input data, denotes an average height of central piers of the bridge. In case of single span structures, the mean height of piers is an average value of the height of end piers. The situation is similar with the bridge span when regarded as an input parameter. This value also had to be unified as it is not the same if there are many small spans, or if there is a smaller number of larger spans, for the same bridge length. Because of this fact, the bridge span, when considered as an input parameter, implies the mean value of the span. Input data with their limit and mean values are presented in Table 1.

With regard to the total cost of construction work, the significant work items are scaffolds and formworks. However, in the analysis, the price of scaffold and formwork is included in the work items that are related to concreting of individual elements of the structure, and are not explicitly stated. That is why it was impossible to analyse costs related to these work items through bills of quantities and cost estimates. Consequently, an input variable covering the bridge construction technology was introduced. The formwork on fixed scaffold and the formwork on mobile scaffold were used during realisation of bridges analysed in this research. The input variable called *Construction technology* was introduced to enable understanding of the influence of these types of work on construction costs. This variable is equal to 0 in case of formwork on fixed scaffold, while it amounts to 1 when the formwork on mobile scaffold is used.

In addition to the above mentioned bridge characteristics, the information on bridge foundations is also used in cost estimation. The cost of foundations is dependant of the foundation method used in a particular case. The foundations of the bridges whose data are used in this research are either shallow, deep, or combined.

Table 1. Input data

Input data No.	Description of input data	Type of data	Unit	Min.	Max.	Mean value
Input 1	Bridge length	Numerical	m	11.50	784.40	153.25
Input 2	Bridge width	Numerical	m	6.50	30.55	11.52
Input 3	Pier height	Numerical	m	2.80	35.90	13.65
Input 4	Bridge span	Numerical	m	11.33	44.50	24.07
Input 5	Construction technology	Category-based (discrete)	-	0	1	-
Input 6	Foundation method	Category-based (discrete)	-	0	2	-

Table 2. Output data

Number of output data	Description of output data	Type of data	Unit	Min.	Max.	Mean value
Output 1	Total construction cost	Numerical	EUR/m ²	409.63	1752.36	915.97

Thus an input variable called *Foundation method* is introduced to take into account the influence of costs that are related to foundations. The value of 0 is attributed to this variable in the case of shallow foundations, the value of 1 is attributed in the case of deep foundations, and the value of 2 is applied in the case of combined foundations.

The data that are used for forming the prognostic model must be comparable to one another. As this is a cost estimation, and as the projects were realised in a period of six years, it was indispensable to carry out the reevaluation of prices.

The change in an average gross salary and the index of increase in the price of construction materials (cement and reinforcement) in the region were checked for the period from 2010 to 2016 during which these projects were realised. Changes in gross salaries were registered in that period in Montenegro. In fact, an average gross salary in construction sector amounted to € 634 in January 2010. In January 2016 the gross salary amounted to € 666. The total change is 5 %. Consequently, it can be concluded that the change in an average gross salary was not significant and that it can be neglected. In the Federation of Bosnia and Herzegovina, an average gross salary over the same period increased from € 391 (767 KM) for 2010 to € 410 (KM 803) for 2016. Thus the change is also around 5 %. In the Republic of Serbia, an average gross salary varied from € 398 (RSD 40,985) for 2010 to € 464 (RSD 57,282) for 2016, which is an increase of 16 %.

To determine the change in the price of construction material, appropriate data were collected from the countries in which the projects were realised (Montenegro, Serbia, and Federation of Bosnia and Herzegovina). After the data collection and calculation, it was established that the price of cement actually reduced and this in Montenegro by approximately 2.7 %, in Serbia by 1.2 %, and in the Federation of B&H by 5.6 %. As to the price of steel reinforcement, it was reduced in Montenegro and the federation of B&H by 13.3 % and 17 %, respectively, while the price of steel reinforcement increased in Serbia by 15.2 % [26].

Due to an insufficient quantity of data and considering that the ratio of material and work to the total price is 45 % to 55 % [27] or

40 % to 60 % (as this is the bridge structure), the decision was made to propose a rough estimate of the change in price. Thus the prices were revalued and at that point the data were ready for input.

After definition of input data for the model, the model output data were also defined. Based on the scope of research, a single output of the model was defined, and this output is the total cost of construction of integral road bridges, cf. Table 4.

When forming the model by means of artificial neural networks, the available data have to be divided into two groups. One of these two groups is the training set that will be used for training-learning the network model, and the other is the test set which will be used for checking the network model. Recommendations for forming these sets are available in the literature. A considerable number of authors select data using the ratio of 90 % to 10 %, 80 % to 20 %, 85 % to 15 %, or 70 % to 30 % [28]. Of course, there are situations in which this ratio is determined based on specific features of the problem to be solved. In this research, the ratio of training to test data will be 80 % to 20 %. In two models, the data will be selected at random, while in six models the data will directly be divided into training and test data. The cross validation procedure (*KFold-CrossValidation* and *LeaveOneOut-CrossValidation*) will be realised through random selection of data.

Once the data have been divided into sets for training and testing, and before the start of the training-learning network, the data contained in the database must be prepared so that they all are situated within an appropriate range, i.e. the data scaling must be performed. The selection of scaling range for input and output data depends on activation of the function of output values. The scaling can be performed by means of standardisation and normalisation [29]. These methods enable reduction of appropriate data to the same order of magnitude. In addition, they enable analysis of the data of similar significance during formation of the model, which means that the analysis of data with smaller range of values will thus be enabled. The data scaling was conducted for the entire set of 113 projects. The following methods were used in this research: Standard Scalar (Z-score normalisation) and Min-Max normalisation.

Table 3. Multilayer perceptron activation functions of artificial neural network models

Function	Designation	Explanation	Scope
Identity	x	Used in output layer only.	$(-\infty, +\infty)$
Rectified linear unit function (ReLU)	$\max(0, x)$	The neuron activation is transferred directly as output if it is positive and, if it is negative, the transfer is 0. It has been proven to have six times better convergence compared to hyperbolic tangent function	$(0, +\infty)$
Hyperbolic tangent function	$\frac{2}{(1+e^{-2x})} - 1$	Similar to sigmoid function, but exhibits better performance due to its symmetry. Ideal for MLP ANN models, and for hidden neurons in particular.	$(-1, +1)$

The network architecture must be defined at the initial model forming phase [30]. The network architecture implies definition of the number of layers and the number of neurons in each layer. Some authors recommend that no more than two hidden layers be defined during definition of the artificial neural network [28, 31, 32]. Networks with such architecture have provided very reliable results, as confirmed by many theoretical results and numerous simulations in a number of engineering disciplines. However, theoretical results also show that no more than one hidden layer is needed for sufficiently accurate network based approximation of any complex nonlinear function [33].

For the time being, there is no accurate and reliable way for selecting the number of neurons. In fact, the number of neurons should be such that it enables expression of the most useful characteristics that the data possess. Big number of neurons results in the overfitting problem, while an insufficient number of neurons leads to poor approximation of the dependence between the input and output values, i.e. it leads to the underfitting problem. However, recommendations do exist for the top limit of the number of neurons in the hidden layer. One of recommendations for the definition of the number of neurons is given in expression (1) [34], while a recommendation for the maximum number of neurons is given in inequality (2) [35]. It would be appropriate to adopt a smaller number from the mentioned inequalities, in which is the number of input parameters and is the number of samples for training.

$$N_H \leq 2 \cdot N_i + 1 \quad (1)$$

$$N_H \leq \frac{N_s}{N_i + 1} \quad (2)$$

The aim is to define the model with the best possible generalization. Generalization is the process in which the knowledge applicable to a set of cases is transferred to one of its subsets [36], i.e. it is the possibility of the model to provide satisfactory values based on the data that were not presented to it during the training (validation set). The validation set is introduced so as to avoid the problem of overfitting or to define the points in which the training process is stopped [37]. An increase in generalisation level during prediction can also be achieved through an alternating validation process. This process is conducted on the data belonging to the testing set.

The performance measurement is conducted during the process of defining the model that is capable of providing the best possible generation. The performance measurement is the prediction of

accuracy. The measurement of accuracy is often defined through the prediction error, which is the difference between the real (desired) value and the predicted value. Several such measurements of prediction accuracy can be found in literature. Some of the most frequently used methods are the mean absolute error (MAE), mean squared error (MSE), mean absolute percentage error (MAPE) and percentage error (PE). In this research, the accuracy of the model was determined by means of the mean absolute percentage error (MAPE) and percentage error (PE). If the deviation between the predicted and expected results in the training set and test set is small, then it can be said that a satisfactory possibility of generalisation has been achieved in the model. The prediction model was formed using the computer program Python 3.7. As the subject of this research is the cost estimation model, and as this issue concerns regression problems, an appropriate multilayer perceptron MLP was formed. The MLP is a type of artificial neural network which, in addition to classification problems, is capable of solving regression problems as well.

The most frequently used neuron activation functions in hidden layers are the sigmoid or logistic activation function, Tanh or hyperbolic tangent activation function, and the ReLu (rectified linear unit) activation function. The activation function of output neurons is mostly linear. According to mentioned recommendations, and taking into account the number of data and their other characteristics, the functions used for hidden neurons in the formation of the model are the rectified linear unit function (ReLU) and the hyperbolic tangent function (Tanh), while the identity function was used for output neurons, cf. Table 3.

4. Results

Artificial neural network models of multilayer perceptron (MLP) class were formed based on the defined input and output variables and other necessary parameters. The number of layers was defined based on recommendations, and the number of neurons in hidden and output layers was defined based on the number of input and output variables. The greatest number of hidden neurons taken in models was 13, as based on expressions (1) and (2). A total of eight models of artificial neural networks were formed. The data scaled according to the StandardScaler procedure were used in one half of these models, while the Min-Max method was used in the other half. All neural networks, NM1, NM2, NM3, NM4, NM5, NM6, NM7 and NM8 each have 6 input variables and 1 output variable. Neural network models with StandardScaler standardisation are shown in Table 4. Characteristics of each model are also indicated, including

Table 4. Artificial neural network models (StandardScaler)

Model name	Model characteristics	Activation function of hidden layers	Activation function of output layer	MAPE training set [%]	MAPE test set [%]
NM1	MLP 6-4-1	Tanh	Identity	16.25	14.15
NM2	MLP 6-7-1	ReLu	Identity	17.21	13.40
NM5	MLP 6-13-1	ReLu	Identity	19.50	14.44

Table 5. Artificial neural network models (Min-Max normalisation)

Model name	Model characteristics	Activation function of hidden layers	Activation function of output layer	MAPE training set [%]	MAPE test set [%]
NM3	MLP 6-5-1	ReLu	Identity	20.79	16.70
NM4	MLP 6-8-1	Tanh	Identity	22.66	19.58
NM6	MLP 6-12-1	ReLu	Identity	18.66	17.26

Table 6. Artificial neural network models with random selection of data (kFold-CrossValidation, k=10)

Model name	Data scaling procedure	Model characteristics	Activation function of hidden layers	Activation function of output layer	MAPE [%]	σ [%]
NM7	StandardScaler	MLP 6-13-1	ReLu	Identity	18.31	5.17

Table 7. Artificial neural network models with random selection of data (LOOCV)

Model name	Data scaling procedure	Model characteristics	Activation function of hidden layers	Activation function of output layer	MAPE training set [%]	MAPE test set [%]
NM8	Min-Max	MLP 6-7-1	ReLu	Identity	17.12	17.06

the accuracy measurement given through the mean absolute percentage error (MAPE)

The following three NM models were formed with scaled data using the Min-Max normalisation procedure. The data about characteristics of the models and the estimation accuracy, determined using the mean absolute percentage error (MAPE), are shown in Table 5.

Two models in which the random selection of data was made using the kFold-CrossValidation for $k=10$ and LeaveOneOut-CrossValidation (LOOCV), and in which the estimation accuracy was determined by the mean absolute percentage error (MAPE), are presented in Tables 6 and 7. In the model in which the classification of data was made with the kFold-CrossValidation, the data were scaled using the StandardScaler, while in model in which the classification was made with LOOCV, the data were scaled using the Min-Max function. The two models that gave the best result are presented here.

It can be seen by comparing these models that the NM2 model exhibits the highest estimation accuracy. In this model, the data are scaled using the StandardScaler. Three neuron layers are defined in the NM2 model. One is the input layer, one is the hidden layer, and one the output layer. There are seven neurons in the hidden layer. The hidden layer activation function is the rectified linear unit function (ReLu). The model estimation accuracy is expressed through the mean absolute percentage error and it amounts to 13.40%. The obtained MAPE value meets the target accuracy of ± 15

%. This model was selected for the final model, and it was used as the basis for defining the prognostic model for estimation.

The fact is that input values exert different levels of influence on estimated values. The level of influence is defined through the analysis of sensitivity. This is the method that helps in defining the cause and effect relationship between the input and output values. The results obtained by this method are presented in Figure 3, i.e. the influence of all six input values on the output value is presented.

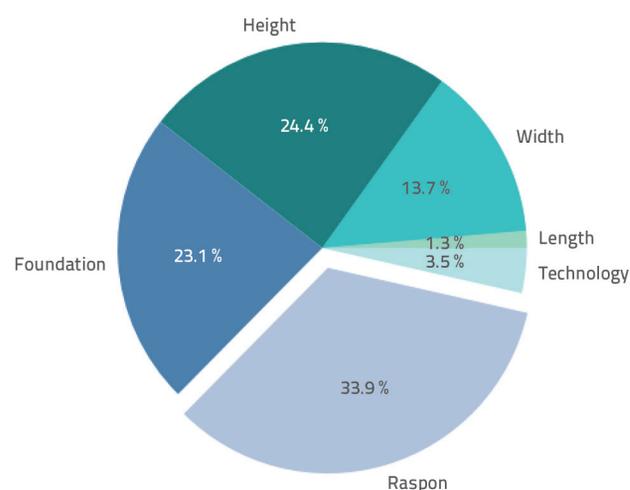


Figure 3. Influence of input values on the output value – bridge price

This diagram shows that the input value that exerts the greatest influences on the bridge price (output value) is the bridge superstructure.

5. Conclusion

Considering the results presented in this research, it can be concluded that the model presenting greatest accuracy in the estimation of construction costs of integral road bridges, is the artificial neural network model whose architecture is represented with three neuron layers, out of which six neurons in the first layer, seven neurons in the second hidden layer, and one neuron in the last output layer. The activation function of the hidden layer of neurons is the rectified linear unit function (ReLU), while the output layer activation function is linear (Identity). The accuracy is presented through the mean absolute percentage error (MAPE), and it amounts to 13.40 %. The input value that exerts the greatest influence on the bridge construction cost is the bridge span and, expressed in percentage values, it amounts to 33.90 %. A greater quantity of data in the database would additionally improve prediction accuracy of the model. In addition, by extending the database with additional properties of structures such as the type of cross section, height of cross section, number of spans, number of piers, structural system, etc.,

would certainly enable wider application of prediction models. Potential parameters that could extend the database would be, in effect, input parameters of the prediction model. The extension of database by adding characteristics of the future structure, or by adding available information that represents some limitations regarding construction of the future structure, would enable creation of an estimation in the phase that precedes preparation of the preliminary design. Some of such data are characteristics of the obstacle – existence or non-existence of a watercourse, riverbed depth, foundation conditions, etc. If it would be possible to achieve at that early phase the estimation accuracy that would roughly correspond to the accuracy realised in this research, then the cost estimation error in early phases of project realisation would be even lower. The prediction model could be useful to both the client and the contractor. In early phases, the quantity of available data about future structures is quite low, and so the cost estimation error is greater compared to estimations made in later phases of the project. The model application depends on the data that are available at the time the estimation is made. That is why input values must be adjusted to the data that are in effect at our disposal. The significance of estimation in early phases lies in the fact that the results of precisely this early estimation greatly impact our decision to participate or not to participate in the realisation of the project.

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