Građevinski materijali i konstrukcije
Building Materials and Structures
journal homepage: www.dimk.rs

https://doi.org/10.5937/GRMK2400003B

Technical paper

The impact of pier height on the construction costs of integral road bridges: An application of artificial intelligence

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Article history

Received: 26 April 2024
Received in revised form: 22 May 2024
Accepted: 24 May 2024
Available online: 24 June 2024.

Keywords

artificial intelligence;
neural networks;
integral road bridges;
costs;
pier height;
impact

ABSTRACT

There are multiple definitions for integral road bridges. One of them explains that these are single-span bridges without expansion joints or bearings at the discontinuity locations. In terms of durability and maintenance, discontinuity locations are considered to be construction parts most exposed to damage in this type of structure. Engineers' efforts to lower maintenance costs and extend the durability of structures have led to the emergence of integral bridges. Early assessment of construction costs is crucial in determining the justification for constructing such structures, as it allows both the investor and the contractor to gauge their involvement in the project's implementation. The construction costs can be determined based on the structure characteristics. One of the major characteristics of integral bridges is the height of their piers. This paper examines how the pier height affects the construction costs of integral road bridges. The prognostic model in the Python 3.7.6 software package applies neural networks to determine the impact of pier height. According to the research, the pier height accounts for up to 20% of the total construction costs of integral road bridges.

1 Introduction

Each structure is unique and has its own specificities. Many factors influence the construction costs of these structures. An estimate of the cost for each of the structures implies quantification of all the elements or resources that are an integral part of the construction and which are necessary for its completion. Determining the impact of any of the elements participating in the total sum is particularly challenging in the early stages of the project.

Numerous definitions exist for integral road bridges. These are single-span structures with no expansion joints or bearings at the discontinuity locations. Moreover, these bridges represent a continuous frame without expansion joints and bearings only above the medium piers. For this type of bridge, the engineers also use the name semi-integral bridges.

This type of bridge is easier to maintain, experiences fewer damages, has a longer lifespan, and enhances traffic safety. The primary cause of damage stems from discontinuity locations, which are either non-existent or absent in these bridges situated over medium piers. These bridges are constructed in monolithic, or prefabricated-monolithic, style.

The integral bridges consist of the span structure, piers, and bridge equipment. Each of these parts generates certain costs during the construction process. As the project progresses, the quantity and quality of data relating to bridge parts change. At the onset of project implementation, there is a limited amount of information available, and its reliability is lower. However, the possibility of an impact on expenses is the greatest in these early stages of project implementation. The impact on expenses decreases as the project progresses (Figure 1). The information we have allows us to accurately determine the impact of each factor on the cost. This is why determining the impact of any factor on the total cost of construction at an early stage of bridge realisation presents a greater challenge.

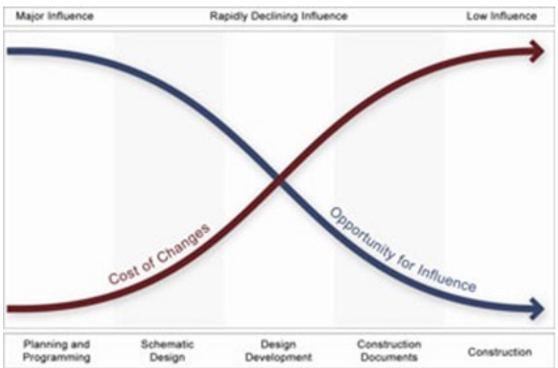

Figure 1. Cost-effective time to make changes [1]

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This study demonstrates the effect of pier height on the cost of building integral road bridges The defined prognostic model for construction cost estimation has been used for analyzing the impact.

1.1 Application of artificial neural networks in construction

The publication of Adeli and Yeh's work [2] in the journal Microcomputers in Civil Engineering in 1989 marked the beginning of the application of neural artificial networks in construction. From its inception until today, the application of neural networks has grown. The reason for their wide application lies, on the one hand, in the wide range of possibilities they have and, on the other hand, in the very rapid development of software packages that provide users with a more comprehensive application.

One possible application of neural networks in civil engineering is to define prognostic models to estimate the cost of different types of building structures. There are a large number of papers in the literature that present different models for cost estimates [3, 4, 5, 6, 7, 8, 9, 10, 11].

M. O. Sanni-Anibire, R. M. Zin, and S. O. Olatunji developed a model for estimating the cost of building construction structures in the early stages of the project using artificial intelligence techniques. The authors defined 12 models and determined their performances. The authors present the performances using Root Mean Squared Error (RMSE =6.09) and Mean Absolute Percentage Error (MAPE = 80.95%) [12].

S. Nirajkumar, J. P. Shah, Z. H. Shah, and M. S. Holia focused their research on estimating the costs of the structures that are part of the road infrastructure during the early design stages. The research resulted in the identification of appropriate factors that are easily available in the early stage and are used for fast, simple, and accurate enough cost estimates [13].

S. K. Magdum and A. C. Adamuthe developed a prognostic model for estimating construction costs. Four models of neural networks (NN) and 12 multi-layered perceptron models (MLP) were compared. MLP and NN give better results than the statistical regression methods. Compared to NN, MLP functions better on a training data set, which is not the case with a test set. Five functions for activation were tested to identify an appropriate function for the problem. The "Elu" activation function gives better results than other activation functions. The study showed that the RMSE values for multiple linear regressions, NN, and MLP were 62.6269, 41.69, and 28.49, respectively. MLP performance is better than that of NN and statistical multiple regression [14].

G. H. Kim, S. Hoon An, and K. Kang examined the performance of three cost estimation models. The trials were based on multiple regression analysis (MRA), neural networks (NN), and case-based reasoning (CBR) using 530 cost data points. NN provided the best estimation model compared to MRA or CBR estimation models. On the other hand, the CBR estimation model outperformed the NN estimation model in terms of long-term use, available results information, and time-to-accuracy ratios [15].

2 Materials and Methods

To consider the impact of the pier height on the cost of the construction of integral road bridges, a model was defined for estimating the estimated construction expenses.

The process of defining the prognostic model involved a number of steps. Figure 2 illustrates the stages involved in defining the model.

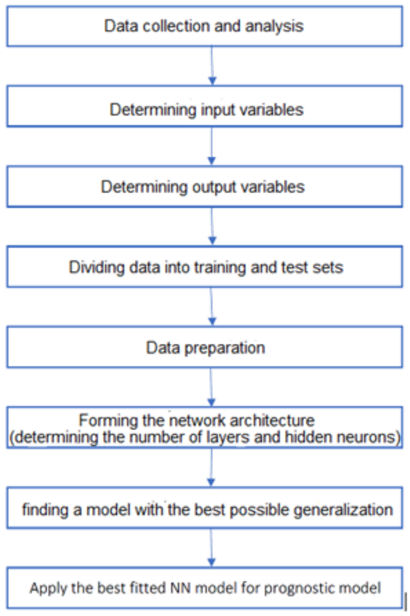

Figure 2. Stages in defining a prognostic model

The 101 main designs of integral road bridges built in the territories of Montenegro (48), Bosnia and Herzegovina (29), and Serbia (24), provide the data used to define a prognostic model. [16]

All the required data were analyzed from the bill of quantities and cost estimates of all the designs. Because the designs were made in three different countries and their forms differed, unifying data was required. To overcome differences, the same types of work were taken from the bill of quantities and cost estimates.

The next stage represents determining input variable models. The criteria for choosing input variables was their impact on the cost of the integral road bridge construction. Research has established that the Pareto distribution governs the behavior of reinforcing and concrete works, indicating their significant and costly nature. Based on this, we selected bridge design characteristics such as bridge length, bridge width, bridge pier height, and bridge span to directly influence cost. In addition to these, as the input variables of the model, the building technology and foundation method were taken, since it is known that they greatly influence the formation of the construction price.
Table 1 shows the input variables of the model with their minimum, maximum, and mean values. The bridges' lengths range from 11.5 to 784.4 m. The bridges are 6.5 to 30.55 m wide. The variable “pier height” represents the mean value of all the piers, and the bridge span implies the mean value of all spans. For the input variable “Construction technology” the following values are assigned: 0.25, 0.5, 0.75, and 1, depending on the pier height. The input variable "Foundation" has been assigned values 0, 1, and 2 depending on the founding methods, which are: 0 in the case of shallow foundation, 1 in the case of deep foundation, and 2 in the case of combined foundation.

Table 1. Input data[11,16]

No input data	Input data description	Data type	Measurement unit	Min	Max	Mean value
Input 1	Bridge length	numerical	m	11.5	784.4	153.25
Input 2	Bridge width	numerical	m	6.5	30.55	11.52
Input 3	Pier height	numerical	m	2.8	35.9	**13.65**
Input 4	Bridge span	numerical	m	11.3	44.5	24.07
Input 5	ConstructionTechnology	discrete	-	0	1	-
Input 6	Foundation	discrete	-	0	2	-

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In addition to defining input variables, it was necessary to determine output variable models. Since the research aimed to define the impact of pier height on the price of the construction of integral road bridges, it is necessary to predict the cost of construction. Based on that, it has been determined that the output variable is the construction cost of integral road bridges (Table 2).

All the data were then divided into training and test sets. Apart from recommendations from the literature [17], we determine the number of data sets for each of these two sets based on the unique nature of the problem we are solving. In defining this model, the percentage ratio of data belonging to the training set to the test set was determined to be 70% to 30%. We selected data for the training and test sets in two ways: directly and through cross-validation procedures. Cross-validation procedures randomly selected the data.

It is necessary to prepare the data for entry into the software after dividing the data into two sets. Data preparation represents their transformation into quantities that are within a certain range. The literature [18] provides several methods for data transformation. The data transformation methods used in this study are Standard Scalar (Z-score normalisation) and Min-max normalisation.

Determining the network architecture means determining the number of layers and the number of neurons in each layer. Only one hidden number is enough to solve almost all the problems [19]. Several criteria exist for determining the number of neurons [19].

- The number of hidden neurons should be in the range between the size of the output layer and the size of the input layer $n_i<n_h< n_o$ (1)
- The number of hidden neurons should be equal to the sum of 2/3 of the size of the input layer and the size of the output layer $n_h=2/3 * n_i + n_o$ (2)
- The number of hidden neurons should be smaller than the double size of the input layer $n_h< 2 * n_i$(3)

where n_i represents the number of neurons in the input layer, $n_o$is the number of neurons in the output layer, and $n_h$is the number of neurons in the hidden layer.

After determining the network architecture, the next step involves identifying a model with good generalization, i.e., a model that produces sufficiently precise results based on unknown data. The model has a good possibility of generalisation when the predicted deviations from the expected results are small.

During the training of the model, its accuracy of prediction is constantly checked, i.e., model performance is measured. The performance of the models in this study was measured via MAE (Mean Absolute Error).

The Python 3.7.6 software package formed the prognostic model. We created a Multi-LayerPerceptrone MLP (Multi-LayerPerceptrone) to define the model.

Activation functions that are used for defining models are: for hidden neurons – the Rectified linear unit function (ReLu), hyperbolic tangent (tanh), and Swish, and for output neurons, the identity function was used (Table 3).

After selecting a model with the best performance, the final model is trained and recorded, and based on that, the prognostic model is defined for estimating the construction price of integral road bridges.

Table 2: Output variable of the model [11]

No of output data	Output data description	Data type	Measurement unit	Min	Max	Mean value
Output 1	Construction cost	numerical	€/m²	409.63	1752.36	915.97

Table 3. Activation functions of a multilayer perceptron model of an artificial neural network [18]

Function	Mark	Explanation	Range
Identity	x	Only in the output layer	$(-\infty, +\infty)$
Rectified Linear units	$max(0, x)$	The activation of neurons is transmitted directly as an output if it is positive, and if it is negative, 0 is transmitted. It has been proven to have six times better convergence compared to the hyperbolic tangent function.	$(0, +\infty)$
Hyperbolic tangent	$\frac{2}{(1+e^{-2x})} - 1$	Activation of neurons is transmitted directly as an output if it is positive and if it is negative 0 is transmitted.	$(-1,1)$
Swish	$x * sigmoid(x)$	A function that is nonlinearly interpolated between a linear and a ReLu function	$(0, x)$

3 Results and Discussion

Models of artificial neural networks are defined, taking into account all the necessary parameters. We adopted the network architecture based on the above recommendations. All neural networks have one input, one hidden, and one output layer. In the input layer of the network, they have six input variables, i.e., six neurons, and one output variable in the output layer, i.e., one neuron. Based on expressions (1), (2), and (3), the hidden layer adopted a maximum number of hidden neurons of five (Table 4).

The training results and characteristics of the artificial neural network models that showed the best performance are given in Tables 5 and 6.

For random choice of data, Cross-validation methods are used (kFold-CrossValidation and LeaveOneOut-CrossValidation - LOOCV). The values of model performance measures that gave the best results, as well as their characteristics are given in Tables 7 and 8.

Table 4. Artificial neural network architecture

Description	Number
Number of hidden layers	1
Number of neurons in the input layer	6
Number of neurons in the output layer	1
Max number of neurons in a hidden layer	5

Table 5. Artificial neural network models for construction cost estimation (StandardScalar)

Model name	Model characteristics	Activation function of hidden layers	Activation function of output layer	MAETraining set [%]	MAE Test set [%]
NN1	MLP 6-3-1	ReLu	Identity	0.0922	0.0752
NN6	MLP 6-5-1	Tanh	Identity	0.0547	0.0855
NN7	MLP 6-3-1	Swish	Identity	0.0866	0.0677

Table 6. Artificial neural network models for construction cost estimation (Min-Max normalization)

Model name	Model characteristics	Activation function of hidden layers	Activation function of the output layer	MAETraining set [%]	MAE Test set [%]
NN12	MLP 6-5-1	ReLu	Identity	0.0873	0.0920
NN13	MLP 6-3-1	Tanh	Identity	0.0993	0.0963
NN18	MLP 6-5-1	Swish	Identity	0.0940	0.0865

Table 7. Artificial neural network models with random data selection for construction cost estimation (kFold-CrossValidation, k=10)

Model name	Data scaling procedure	Model characteristics	Activation function of hidden layers	Activation function of the output layer	MAE Test set [%]
NN21	StandardScalar	MLP 6-5-1	ReLu	Identity	3.84

Table 8. Artificial neural network models with random data selection for construction cost estimation (LOOCV)

Model name	Data scaling procedure	Model characteristics	Activation function of hidden layers	Activation function of the output layer	MAE-Training set [%]	MAE Test set [%]
NN23	Min-Max	MLP 6-4-1	ReLu	Identity	0.0839	0.0932

We selected the model with the highest accuracy and the best prediction performance after a comparative analysis of all results. This is the NN7 model. In this model, the data were transformed by the StandardScaler method. The number of hidden neurons is three. Figure 3 displays the neural network architecture. The activation function is called Swish. The prediction expressed through MAE has an accuracy of 0.0677.

The model with the highest accuracy was chosen to form the final model for estimating the cost of building integral road bridges, and based on it, prognostic models were defined.

Based on the finally developed prognostic model, the impact of the pier height on the integral road bridge construction price has been analysed (Figure 4).

The diagram shows that the variable "Pier height" accounts for about one fifth of the total construction price, or, in other words, about 20%.

From the diagram of the change in the price of construction depending on the height of the bridge piers (Figure 5), it is clear that the price of construction increases to a certain value of the pier's height. As the pier height increases, the construction costs do not significantly change.

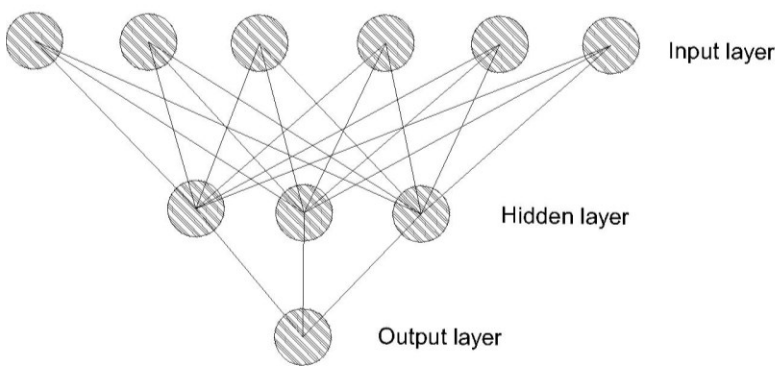

Figure 3. Artificial neural network architecture with the best performance

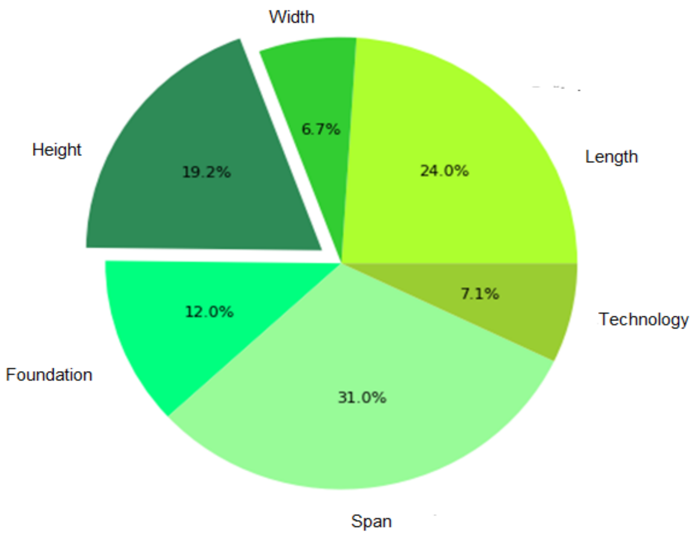

Figure 4. Impact of the input variable "Pier height" to the cost of integral road bridges construction

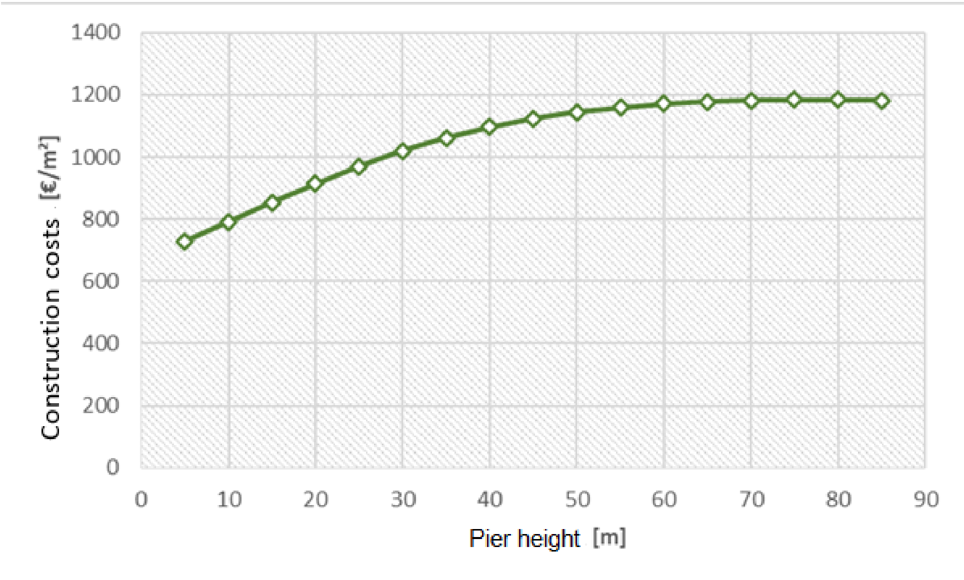

Figure 5. Change in the construction price depending on the pier height

4 Conclusions

The research results show that the model with the best performance is a model of an architecture of three layers: one input, one hidden, and one output layer. There are six neurons in the input layer, three neurons in the hidden layer, and one neuron in the output layer. The Swish function is the activation function of the hidden layer of neurons. The output layer has an activation function called Identity, i.e., a linear function. The mean absolute error (MAE) measured the prediction accuracy, and in the model with the best accuracy, it was 0.0677.

The prognostic model was defined based on the model that presented the best results in forecasting. Upon analysing the results and behaviour of a prognostic model, we observed that pier height accounts for 19.2% of the total sum. Furthermore, forecasts obtained in a specific case from the prognostic model indicate that the price of bridge construction has a growing trend until a certain pier height, and after that, the cost per meter square is slightly increasing.

The height of piers influences the choice of construction methods and technology. The piers can be cast in concrete in situ (depending on which types of piers they belong to, abutments or medium ones), or they could be made by using fixed, immovable, or sliding formwork. It is possible to incorporate the stated technologies for pier construction into the prognostic model, appropriately, and show the impact of the piers' height on the construction price. The results obtained in this way could be used to conduct a comparative analysis with the results of the model presented in this paper, thus determining the impact of the pier height on the price of bridge construction with even greater accuracy.

Author Contributions:

Conceptualization, Ž.B. and M.K.; Data curation, Ž.B; Formal analysis, Ž.B; Investigation, Ž.B.; Methodology, Ž.B. and M.K.; Project administration, Ž.B. and M.K.; Resources, Ž.B. and M.K.; Software, Ž.B.; Supervision, Ž.B. and M.K.; Validation, Ž.B. and M.K.; Visualization, Ž.B.; Roles/Writing—original draft preparation, Ž.B.; Writing—review and editing, Ž.B. and M.K.;

Conflicts of Interest:

The author declare that there is no conflict of interest regarding the publication of this paper.

Acknowledgments:

The research was not supported by others.

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