Construction Cost Estimation of Brazilian Highways Using Artificial Neural Networks

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***Abstract*—Estimating costs of construction projects more accurately at the project development stage is crucial for feasibility studies and it is a key factor for their success. Construction costs are often underestimated and recent statistical studies show that errors in cost estimation have not diminished. This paper focuses on the development of a more accurate estimation technique for construction highway projects using Artificial Neural Networks. Different architectures of the network with 10, 15, and 20 neurons were trained and tested with the backpropagation algorithm. Based on this, data from fourteen highway projects in Brazil were collected and analyzed. Eleven parameters that contribute the most to the construction final budget were found after trials and errors. For the best scenario, an average cost estimation accuracy of 99% was achieved. This preliminary study showed the feasibility of the tool applied to projects in Brazil and may be used by public agencies in the future.**

***Index Terms*— Artificial Neural Networks, construction, cost estimate, highway projects.**

I. Introduction

It is known that public projects, such as infrastructure projects, are usually associated with delays in completion as well as costs higher than estimated. These projects involve many uncertainties and, historically, have a high rate of failure.

Reference [1] observed that if inaccuracy of the initial cost estimates was simply a matter of incomplete information and inherent predictive difficulties, as said by those responsible for project estimates, then these inaccuracies would be expected to be random. Apart from that, the authors affirm that there are four types of explanations for costs underestimation: technical, economic, psychological and political.

According to [1], costs are underestimated in almost 9 out of 10 transportation infrastructure projects and actual costs are on average 28% higher than estimated. For road projects, costs are on average 20% higher than the estimated. In a study of 70 projects carried out by [2], extra costs was identified in more than two thirds. Researchers from another study [3] analyzed 152 public works contracts accomplished between 2008 and 2015 in Brazil, and concluded that 78% made additives of time and/or cost. Cost performance was analyzed on over 800 Canadian Drainage and Maintenance Department construction projects by [4] and they observed a discrepancy of up to 60% between estimated and actual final cost of projects completed between 1999 and 2004.

Excess costs are a major concern for the public and private sectors due to a negative impact in in public funds and profitability, causing great distress among taxpayers and shareholders, and even destabilizing for political parties in power. Road projects are likely to exceed costs, as the contract is closed by the fixed amount of the bid. Changes, errors and omissions in contracts were identified as key contributors to the excess costs of this type of project [5].

For the purpose of estimates optimization, tools and techniques may be divided into three groups: analysis of statistical probabilities, comparison with similar projects, and Artificial Intelligence (AI) techniques. The use of AI has been widely adopted to estimate costs, and Artificial Neural Networks (ANNs) are considered an efficient prediction tool that recognizes past patterns, as well as connections of factors that influence the cost. This way, it is possible to predict the future through trends.

Based on data of fourteen projects executed from 2001 to 2017, the objective of this research was to estimate costs of road projects, based on variables that impact most the cost of the work, using the technique of ANNs to test the pattern recognition and accuracy for the project phase.

II. Cost Estimates

Cost is one of the main criteria in decision making of any construction project. According to the international recommended practice [6], for the purpose of screening, feasibility, concept study, budget authorization or control end usage, the typical estimating method is stochastic or judgment. For later stages of the project, the methodology recommended is deterministic. As the project progresses, the accuracy of the cost estimate increases as details of the project become clearer.

The smallest deviation from the project cost estimate must deal with limited available data, difficulty in defining the relationships between available data and total project costs, and the need to capture unique characteristics of a new project [7].

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The use of the semi-detailed method from quantitative is time-consuming and may be ineffective in the initial project phase, due to design changes that occur frequently [8]. Unit cost and cost per unit area are deterministic methods, and they are based on historical data with project details needed to achieve accuracy.

Regression analysis is a parametric cost estimate, which uses a mathematical relationship between design variables and historical data to predict project cost. This statistical method is used to explore correlations between independent and dependent variables, and its purpose is to identify the most accurate equation of the dependent variable as a linear function of two or more independent variables according to the causal relationships between changes in internal factors. The major difficulty of this method is the accuracy of the cost function.

Reference Class Forecasting (RCF) is a probabilistic method, based on the concept of cognitive bias. To execute the RCF, four steps are required: (1) collection of planned and actual project data; (2) identification of past project reference classes; (3) establishment of a probability distribution for each reference class based on the data collected; and (4) determination of the elevation curve of the optimization bias is required for the reference classes [2], [9]. In the RCF approach, it is assumed that past projects tend to be more similar to planned projects than normally assumed and therefore can be used as a means to increase forecast accuracy. Instead of focusing only on the specific components of the planned projects (the internal view), there should be equal or less focus on the results of similar projects that have already been completed (an external view) [10].

In recent years, researchers in the field of construction [7], [11]–[14] have investigated and developed new models in an attempt to improve cost estimation and forecasting, mainly using case-based reasoning, reference class forecasting, and artificial neural networks.

III. Artificial Neural Network

Artificial Neural Network (ANN) is a technique inserted among the several existing methodologies for the solution of Artificial Intelligence problems, based on the adjustment of sets of parameters (adjustment of weights), making it able to learn, through experiments (training), and generalize the behavior of a given problem. ANNs are used to establish relationships between inputs and outputs with a higher level of complexity through adaptive learning of training examples. After training, the model can be used to predict output based on the input data provided [15]. It imitates structures where calculus is processed through artificial neurons, which are interconnected to form a network, being able to store information, recognize and classify patterns, and make predictions [16].

ANN can be classified as to the activation functions used within them, the architecture, and their learning. In this work, the architecture used was the feedforward network of multiple layers (MLP) and the typical structure of this network is shown in Fig. 1.

Fig. 1 exhibits the grouping of neurons in the input layer, the middle or hidden layer, and the output layer. Input data are processed in the middle layer, so that the neurons in this layer are obtained by means of the product between inputs and weights (αij). In turn, the response processed by the network is the result of the multiplication between the neurons of the hidden layer and the second group of weights (ωkj). The values of the last layer (output) correspond to the solution of the problem. The network maps the relationship between the input data and the output variable based on the activation functions.

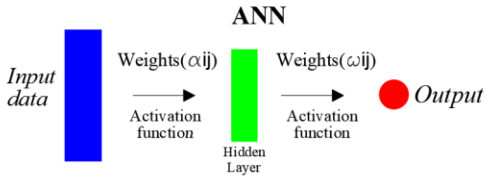

Figure 1. Architecture of the MLP network.

The determination of the ANN weights is made through a procedure called training, performed by the backpropagation learning algorithm. During training, the network obtains outputs, so that they can be compared to the desired results, generating the error. From there, the error is propagated to the previous layers and the process restarts. The network is apt to be generalized when these errors are minimal for the type of problem to be solved. Several input-output examples are presented to the network and its weights are iteratively modified until the ANN is at an acceptable mapping capacity, which is defined by the user.

The amount of neurons may vary according to the problem being solved. Some authors suggest a formulation for the ideal number of neurons, as compiled by [17] according to Table I, where (N_h), ($N_{in,}$ n), (N_p), (N_0), (L), and MSE represent, respectively, the number of neurons in the hidden layer, the number of input variables, the number of projects, the number of outputs, the number of hidden layers, and the Mean Squared Error obtained by simulating each of the configurations.

TABLE I. Estimates of the Optimal Number in the Hidden Layer

Research	Method	Year	Number of neurons in the hidden layer
1	Li et al	1995	$N_h = (\sqrt{1+8n} - 1)/2$
2	Tamura e Tateish	1997	$N_h = N - 1$
3	Fujita	1998	$N_h = Klog\|P_c Z\|/logS$
4	Zhang et. al	2003	$N_h = 2^n/n+1$
5	Jinchuan e Xinzhe	2008	$N_h = \left(N_{in} + \sqrt{N_p}\right)/L$
6	Chen e Xu	2008	$N_h = C_f(N/dlogN)^{0,5}$
7	Shibata e Ikeda	2009	$N_h = \sqrt{N_i N_o}$
8	Hunter	2012	$N_h = 2^n - 1$
9	Sheela e Deepa	2013	$N_h = (4n^2+3)/(n^2-8)$

Several hidden layers can be included. However, cost-prediction studies [15], [18]–[20] used only one layer on the MLP network. The function of the hidden layer is to increase the processing power in order to make the network capable of solving more complex problems.

IV. Methodology

In order to achieve the goal of the study, a methodology was developed in 3 stages. In the first stage, other cost estimation studies using ANN were analyzed, then the design of the model for application in highway construction was defined. In the final stage, the model was tested to investigate the best network configuration in order to obtain greater accuracy. The stages will be presented in the following sections.

A. Application of Artificial Neural Network in Cost Estimation

ANN is a viable alternative to predict construction costs because it eliminates the need to find a function that mathematically describes the cost of a system based on the variables that most contribute to this cost [21]. According to [22], neural networks produce better cost predictions than conventional methods if some conditions are met, i.e., the database is sufficient, the parameters for costing are known, and if there are few cost drivers due to the fact that the more parameters are used, the more training samples are required to achieve a given accuracy, but the training samples are usually scarce in cost estimation. Another condition to be met by the same author is that there can be no explicit knowledge about the effects of cost. Neural networks learn from scratch by detecting hidden relationships between training data.

From the point of view of a new product development, [22] found that neural networks seem more appropriate for cost estimation in the conceptual phase for design adaptations, design variations, or improvements of old projects. References [20],[23],[24] show that ANNs performance was better than regression analysis in construction cost estimates.

B. The Design and Modeling Phase

This paper presents a model using backpropagation, which is based on the error correction learning rule. The computational tool used was the Neural Network Toolbox™ that is inserted in the Matlab environment.

Once the input and output variables are defined, the information must be grouped in matrix form and organized in such a way that the network can identify the mathematical relationships between the inputs and their respective outputs. Then, the type of algorithm, the number of neurons, and the functions are defined. After that the training begins followed by the validation and test steps.

In the network training, known data sets are required. Thus, inputs were the most influential variables in the road projects estimation costs, based on data collection from the Brazilian National Department of Transport Infrastructure (DNIT), and the output was the actual cost value of the work. Thirteen projects were used for training and validation, and one project for testing. Several combinations of the input variables were performed to analyze the best configuration. The test example was used to measure the performance of the ANN model. The outputs were also varied because it is possible to provide the value in different ways, such as percentage and value range.

Once the network was trained and presented small errors (calculated by MSE), data that were not known by the system were provided in the validation and testing phase, which are the variables of the problem in question. The statistical performance used to stop training process is the MSE. The error found during this phase is monitored during the training process. When the network begins overfitting the data, the error of the validation step begins to increase and when this happens, for a given number of times, the training is stopped. Overfitting occurs when the model is too complex with insufficient training data or due to excessive training and the result training error is small, but the test error is large.

The performance monitoring was evaluated comparing the network outputs with the actual values by the Magnitude of Relative Error (MRE), as in (1), and the Mean Absolute Percentage Error (MAPE), as in (2).

$$MRE = \frac{|A\text{-}E|}{A} \tag{1}$$

$$MAPE = \left(\frac{100\%}{n}\right)\sum_{i=1}^{i=n}\frac{|A_i\text{-}E_i|}{A_i} \tag{2}$$

where A is the actual cost, E is the estimated cost, and n is the number of data points in the testing data set.

C. Data Analysis and Identification of Variables

Based on the study of [13],[20],[25], the predominant cost drivers of the construction cost were found. Then, these variables were discussed with engineers from DNIT to define the ones that were most suitable for the works in Brazil.

The parameters of the input were defined and analyzed after performing tests based on the network training that provided the smallest errors using trial and error method. These variables are presented in on the study of [13],[20],[25], the predominant cost drivers of the construction cost were found in Table II.

TABLE II. Input Variables

Road extension
Class of the road
Execution time
Average transport distance of steel
Average transport distance of cement
Average transport distance of petroleum asphalt cement
Volume of excavation
Volume of embankment
Volume of bituminous concrete
Number of bridges executed
Extension of the bridges

The length of the highway was given in kilometers (km), the class was defined by track speed in kilometers per hour (km/h), time was given in days, average transport distances in km, excavation, embankment and bituminous concrete volumes were given in tons, and the average length of the bridges in meters (m).

The records of 14 projects contain data from the project design on all of the selected 11 parameters and the corresponding final costs of the road works, which is the only variable in the output layer, as presented in Table III. The values in the table are in the Brazilian currency (Real).

The model included 11 input variables corresponding to the defined parameters, the number of neurons in the hidden layer followed criteria 2 and 5 presented in Table I, resulting in 3 different networks with 10, 15, and 20 neurons. In this way, the network architecture was defined according to the scheme shown in Fig. 2, which represents the network with 10 hidden neurons.

In addition, the activation function used was the hyperbolic tangent (tansig) in the two steps of the neuron processing of the hidden layer and the output of the network. This activation function is in accordance with previous studies on cost estimate [12],[13],[15],[18].

TABLE III. ROAD DATA

Project	Road Extension	Actual Cost
1	30	R$ 42,279,176.94
2	61.4	R$ 100,307,641.74
3	67.3	R$ 95,283,090.49
4	41.5	R$ 57,079,879.18
5	79.3	R$ 37,708,924.89
6	44.1	R$ 57,243,744.10
7	70.9	R$ 98,036,062.24
8	60	R$ 37,023,063.25
9	18.1	R$ 50,862,268.46
10	102.3	R$ 237,365,366.80
11	51.9	R$ 121,351,788.98
12	79.3	R$ 160,047,199.88
13	117.14	R$ 304,268,814.78
14	**45.5**	**R$ 67,211,175.46**

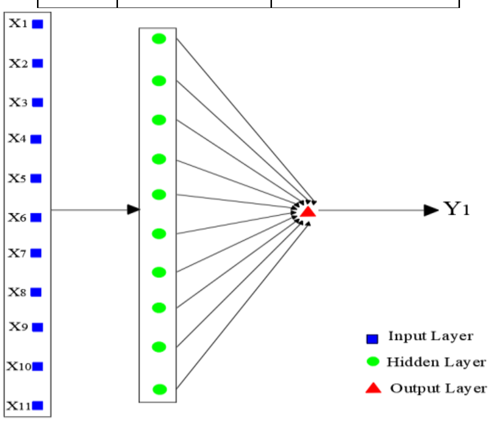

Figure 2. Architecture of the network with 10 neurons.

As mentioned above, the training was carried out from 13 projects. Each project was trained 3 times in order to obtain a convergence. Then, an average training result was taken of each of the 3 network architectures, regarding 10, 15, and 20 hidden neurons.

V. RESULTS

The network training for the estimated cost in each of the architectures and the actual cost is shown in Figure. 3, Fig. 4, and Fig. 5. We can see that there is a tendency of the values being more distorted as the number of neurons increases. The results aim that the network begins to be very trained with the increase of neurons, raising errors. This overfitting can be explained by the small sample size because the algorithm super adjusts the operation of the network specifically for the projects involved in the training. The more projects in the sample training, the greater the range of cases and the probability of obtaining a hit level when one of the examples in the sample goes far beyond the standard is much larger. However, other analyzes need to be done, such as training the network with fewer neurons to observe if this trend remains.

It is worth mentioning that all the variables were normalized by the maximum value of elements approach, in order to avoid wastage of computational resources, besides allowing better optimization of the results.

Data from one project was used for testing purposes. Due to the good training, the 11 input variables for the network simulation were provided, since the weights were already adjusted. Based on the already presented model of the network with 3 different architectures, three tests were carried out in each of them, in order to verify the convergence of the results and to analyze the best configuration for this type of application.

In the first group, regarding the network with 10 neurons, trainings were performed with a mean of 25 iterations, resulting in an average MSE of the order of 10^{-4}. Considering that the network has to pass through the two main phases, being training and testing, in this last phase the 11 variables of project 14 (Table III) were provided and results obtained after the processing were R$ 67,730,238.17; R$ 67,638,957.53; and R$ 66,482,736.03, as shown in Table IV.

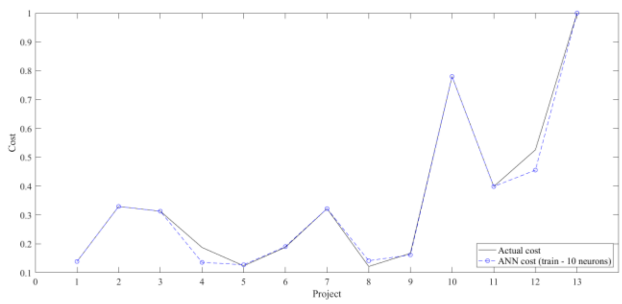

Figure 3. Network training for group 1.

TABLE IV. TEST RESULTS FOR THE 10 NEURONS NETWORK

Test	Actual Cost	ANN Cost	MRE
1	R$ 67,211,175.46	R$ 67,730,238.17	0.8%
2		R$ 67,638,957.53	0.6%
3		R$ 66,482,736.03	1.1%

For the second group, corresponding to the network with 15 neurons in the hidden layer, the average number of iterations was the same as the first group and average MSE was of the order of 10^{-5}. Results of this test are displayed in Table V.

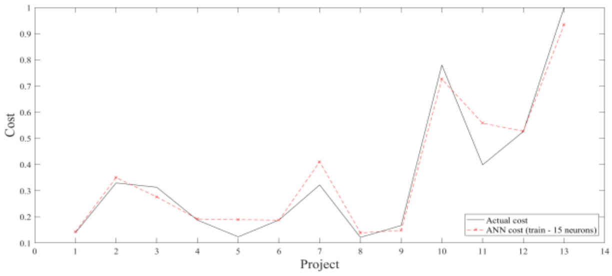

Figure 4. Network training for group 2.

TABLE V. TEST RESULTS FOR THE 15 NEURONS NETWORK

Test	Actual Cost	ANN Cost	MRE
1	R$ 67,211,175.46	R$ 63,379,194.12	5.7%
2		R$ 63,135,779.07	6.1%
3		R$ 63,744,316.70	5.2%

For the third group with 20 hidden neurons in the network, the number of iterations remained the same (25), resulting in an average MSE of the order of 10^{-6}. The results for the 3 tests made are shown in Table VI.

A comparison between the actual cost of the testing example and the obtained result for the 3 groups is displayed in Fig. 6. It can be seen that results from network of group 2 are far from the actual cost and the number of hidden neurons that gave the best result was from group 1 with 10 neurons, followed by group 3, and group 2, respectively, as indicated in Table VII.

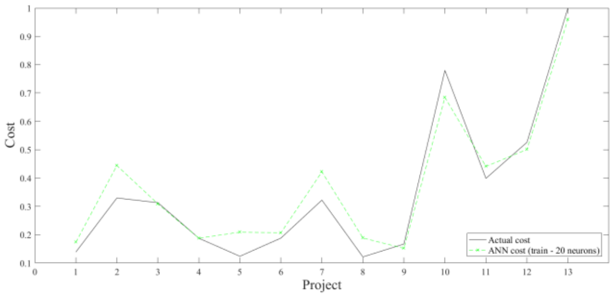

Figure 5. Network training for group 3.

TABLE VI. TEST RESULTS FOR THE 20 NEURONS NETWORK

Test	Actual Cost	ANN Cost	MRE
1	R$ 67,211,175.46	R$ 68,064,933.87	1.3%
2		R$ 66,087,186.57	1.7%
3		R$ 68,886,459.67	2.5%

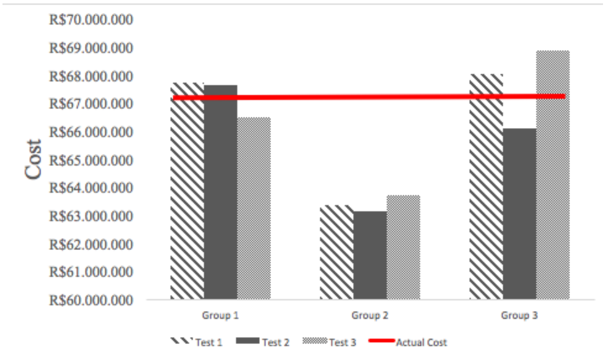

Figure 6. ANN costs x Actual cost.

TABLE VII. AVERAGE RESULTS

Group	Average ANN Cost	Actual Cost	MAPE
1 (10 neurons)	R$ 67.283.977,24	R$ 67.211.175,46	0,8%
2 (15 neurons)	R$ 63.419.763,29		5,6%
3 (20 neurons)	R$ 67.679.526,70		1,8%

These findings show that the best network with the smaller error and the smaller deviation is the architecture with 10 neurons, as the average error was less than 1% and a standard deviation of 0.25. Thus, results indicate that the model has good generalization.

Due to availability of data, these were removed from executive projects, i.e., when the projects were already defined, which does not occur in the early stage. For this reason, the estimation error was small compared to the average acceptable error of estimates based on preliminary draft. Reference [13] predicted the final construction cost of highway projects and found an error of 23%, while [15] obtained 28.2% for engineering services in public construction projects, and the error for road construction in developing countries was 25% by [20]. All of them used ANNs to estimate costs at the conceptual stage. According to [6], the expected accuracy range of cost estimate is between 10% and 30% when the project definition is of 40% maximum.

Results obtained was similar from previous studies, as [25] found an error of less than 5% using 9 input variables and 19 neurons in the hidden layer. Reference [26] obtained 2.5% for forecasting final budget required to finish the construction during construction stage in Thailand using 8 variables and 300 hidden neurons. Both of the studies regarded to highway construction projects.

In addition, study [27] analyzed 80 public construction projects using ANN with the backpropagation algorithm and the hyperbolic tangent (tansig) as the activation function, finding the best network with 3 neurons in the hidden layer. For the performance, authors have found results in accordance with this paper and the MAPE was 2.82% for the construction estimation, whilst [28] found the MAPE equals to 5.84% for the construction material quantities estimation.

VI. CONCLUSION

It is well recognized that greater accuracy of the cost estimation leads to better decision making. This study presented good results, with an accuracy rate of 99%, defined as the difference of 100% and the error (MAPE).

The main objective of this study was to show that artificial neural networks technique can be a great tool for estimating costs, since the value for each of the most influenced input variables on costs found are available. The results confirm that ANN is a promising tool, especially for cases like Brazil, where computational tools are still little explored, requiring a greater time in the execution of tasks as estimates. In addition, less than 50% of Brazilian public projects are in accordance with the planned budget. However, further deeper assessments need to be performed.

The presented study is expected to contribute and support road construction planners, as better analysis can be taken with the 11 parameters provided to be reproduced and applied to other highways.

It is recommended that datasets are expanded on future research to construct more generalized and accurate construction highways estimation model. Also, it could be relevant to study other possible important input variables in order to reduce the number of parameters.

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REFERENCES

[1] B. Flyvbjerg, M. S. Holm, and S. Buhl, "Underestimating costs in public works, error or lie?" *Journal of the American Planning* Association, vol. 68, no. 3, pp. 279–295, Summer 2002.

[2] T. V. Fridgeirsson, "Reference class forecasting in Icelandic transport infrastructure projects," *Transport Problems*, vol. 11, no. 2, pp. 103-115, June 2016.

[3] L. De Andrade and M. T. M. Carvalho, "Levantamento de aumento de custo e prazo de obras públicas de 2008 a 2015," *Simpósio Brasileiro de Gestão e Economia da Construção*, Fortaleza, CE, November 8-10, 2017.

[4] D. P. Alex, M. Al Hussein, A. Bouferguene, and S. Fernando, "Artificial neural network model for cost estimation : City of Edmonton's water and sewer installation services," *Journal of Construction Engineering and Management*, vol. 136, no. 7, pp. 745–756, July 2010.

[5] P. E. D. Love, C. Sing, B. Carey, and J. T. Kim, "Estimating construction contingency : Accommodating the potential for cost overruns in road construction projects," *Journal of Infrastructure Systems*, vol. 21, no. 2, pp. 1-10, June 2014.

[6] J. Bates, et al., *Cost Estimate Classification System*, 2011.

[7] W. C. Wang, T. Bilozerov, R. J. Dzeng, F. Y. Hsiao, and K. C. Wang, "Conceptual cost estimations using neuro-fuzzy and multi-factor evaluation methods for building projects," *Journal of Civil Eng and Manag*, vol. 23, no. 1, pp. 1-14, January 2017.

[8] J. S. Armstrong, *Principles of Forecasting: A Handbook for Researchers and Practitioners*, Pennsylvania: Springer Science & Business, 2001, ch 3.

[9] B. Flyvbjerg, "Over budget, over time, over and over again: Managing major projects," in *The Oxford Handbook of* Project *Management*, 2011, ch 13, pp. 321-344.

[10] E. O. Eythorsdottir, "Reference class forecasting method used in Icelandic transportation infrastructure projects," M.S. thesis, School of Science and Eng., Reykjavík Uni., Reykjavík, Iceland, 2012.

[11] J. Ahn, M. Park, H. S. Lee, S. J. Ahn, S. H. Ji, K. Song, and B. S. Son, "Covariance effect analysis of similarity measurement methods for early construction cost estimation using case-based reasoning," *Automation in Construction*, to be published.

[12] S. Bayram and S. Al-Jibouri, "Efficacy of estimation methods in forecasting building projects' costs," *Journal of Construction Eng Manag*, vol. 142, no. 11, pp. 5016012-5016019, May 2016.

[13] B. J. Gardner, D. D. Gransberg, J. A. Rueda, "Stochastic conceptual cost estimating of highway projects to communicate uncertainty using bootstrap sampling," *ASCE-ASME Journal of Risk Uncertainty in Eng Systems, Part A: Civil Eng*, vol. 3, no. 3, October 2016.

[14] O. Swei, J. Gregory, and R. Kirchain, "Construction cost estimation: A parametric approach for better estimates of expected cost and variation," *Transportation Research Part B: Methodological*, vol. 101, pp. 295–305, July 2017.

[15] K. H. Hyari, A. Al-daraiseh, and M. El-mashaleh, "Conceptual cost estimation model for engineering services in public construction projects," *Journal of Manag in Eng*, vol. 32, no. 1, pp. 1–9, April 2015.

[16] M. Marcy, A. Brasiliano, G. B. L. da Silva, and G. Doz, "Locating damages in beams with artificial neural network," *International Journal of Lifecycle Perform Eng*, vol. 1, no. 4, pp. 398–413, 2014.

[17] K. G. Sheela and S. N. Deepa, "Review on methods to fix number of hidden neurons in neural networks," *Mathematical Problems in Eng*, vol. 2013, June 2013.

[18] M. Arafa and A. Mamoun, "Early stage cost estimation of buildings construction projects using artificial neural networks," *Journal of Artificial Intelligence*, vol. 4, no. 1, pp. 63–75, 2011.

[19] O. Dursun and C. Stoy, "Conceptual estimation of construction costs using the multistep ahead approach," Journal *of Construction Eng Manag*, vol. 142, no. 9, pp. 1-10, March 2016.

[20] J. Sodikov, "Cost estimation of highway projects in developing countries : Artificial neural network approach," *Journal of the Eastern Asia Society for Transportation Studies*, vol. 6, pp. 1036-1047, January 2005.

[21] G. H. Kim, S. H. An, and K. I. Kang, "Comparison of construction cost estimating models based on regression analysis, neural networks, and case-based reasoning," *Building and Environment*, vol. 39, no. 10, pp. 1235–1242, October 2004.

[22] J. Bode, "Neural networks for cost estimation: Simulations and pilot application," *International Journal of Production Research*, vol. 38, no. 6, pp. 1231–1254, April 2000.

[23] M. W. Emsley, D. J. Lowe, A. R. Duff, A. Harding, and A. Hickson, "Data modelling and the application of a neural network approach to the prediction of total construction costs," *Construction Manag and Economics*, vol. 20, no. 6, pp. 465–472, October 2002.

[24] B. R. Setyawati, S. Sahirman, and R. C. Creese, "Neural networks for cost estimation," *AACE International Transactions*, January 2002.

[25] X. Z. Wang, X. C Duan, and J. Y. Liu, "Application of neural network in the cost estimation of highway engineering," *Journal of Computers*, vol. 5, no. 11, pp. 1762–1766, November 2010.

[26] W. Pewdum, T. Rujirayanyong, and V. Sooksatra, "Forecasting final budget and duration of highway construction projects," *Eng, Construction and Architectural Manag*, vol. 16, no. 6, pp. 544-557, November 2009.

[27] G. Polat, B. N. Bingol, A. P. Gurgun, and B. Yel. "Comparison of ANN and MRA Approaches to Estimate Bid Mark-up Size in Public Construction Projects," *Procedia Engineering*, vol. 164, pp. 331-338, June 2016.

[28] B. García De Soto and B. T. Adey, "Preliminary resource-based estimates combining Artificial Intelligence approaches and traditional techniques," *Procedia Engineering*, vol. 164, pp. 261-268, June 2016.

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