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Artificial Neural Networks for Predicting Conventional Cost of Industrial Construction Projects

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Abstract

Artificial neural networks (ANN's) are an important tool for solving complex problems leading to an extensive application in project management. For that purpose, the aim is to develop a model to predict the actual cost of construction projects related to industry infrastructure. A literature review is carried out on the latest research regarding the application of ANN's in the construction industry followed by the relevant findings. Then the research methodology for the implementation of artificial neural networks is presented, and finally construction of ANN based models took place, based on a sample of 20 industrial construction projects.

The most successful models for forecasting actual cost of industrial construction projects are presented and the results are considered satisfying despite the limited amount of case studies. The considered independent variables included: Type of premises, contact with neighboring construction, distance from headquarters (km), project budget (€), initial project duration (days), area of premises (m^2), earthworks (m^3), reinforced concrete (m^3), metal bearing construction weight (tn) and finally average daily number of workers. Finally, ANNs' predicting capabilities is discussed, showing great accuracy, and a number of suggestions are presented for further improvement and future research.

Keywords

Project Management, Project Organization and Planning, Artificial Neural Networks, Industrial Projects, Cost Forecasting.

1. Introduction

Artificial neural networks are mathematical models that belong to the category of empirical capacity models. Their architecture consists of hidden layers with various artificial neural cells that contain activation functions. Several studies focus on project cost, estimates, compensation methods, contract types and artificial neural networks (Anagnostopoulos et al., 2021; Antoniou et al., 2018; Antoniou & Aretoulis, 2019; Aretoulis et al., 2016; Aretoulis, 2019; Titirla et al., 2021; Titirla & Aretoulis, 2019). The term Artificial Neural Networks (ANN) essentially describes several complex mathematical models, which are inspired by the corresponding biological ones. These models attempt to imitate the behavior of neurons in the human brain. Since the beginning of the 19th century, scientists have found that the brain consists of discrete elements, neurons, which communicate with each other and constitute its basic structural element. It is estimated that the brain contains approximately 10 billion neurons arranged in groups, each of which forms a natural neural network (Georgouli, 2015).

An additional definition by Aleksander & Morton (1991) states that: "An Artificial Neural Network is a vast parallel processor with distributed architecture, consisting of simple processing units and naturally capable of storing empirical knowledge and making it available for use." Of course, the way neural networks are used differs from that of classical computers. Their function is based on a combination of the methodology by which the human brain works and the way in which abstract mathematical thinking operates. The network is trained, learns, remembers numerical values, or forgets them, concepts that until now are characterized and concerned only by human thought (Argyrakis, 2001).

Neural networks first appeared about 50 years ago and became a separate interdisciplinary specialty from the mid-80s onwards, a fact that is verified by the large number of scientific publications and applications that began to diffuse in the market. The first artificial neural network built belongs to the neurophysiologist Warren McCulloch and Walter Pits in 1943, but the available technology of the time, put significant restrictions on its satisfactory development. The main reason for the development of neural networks from the moment of their first appearance, which attracted the interest of scientists, was the desire to construct machines and systems capable of carrying out complex operations, which computers based on the von Neumann model do not solve successfully due to their serial mode of operation (Siganos & Stergiou, n.d.). In the next sections the research methodology is highlighted. Then follows correlation analysis and ANN models' creation and conclusions along with future research.

2. Research Methodology and Sample Description

In order to apply artificial neural networks, it was needed to record a number of completed projects. The collection of data was based on several completed industrial projects with a variety of dimensions and uses. These projects were constructed in various regions of Greece and presented separate requirements depending on the desired result. The parameters examined included the type of installation (warehouse, refrigerator storage, freezer storage, offices), the building surface, the volume of earthworks, the surface of the asphalt pavements of the surrounding area, the amount of reinforced concrete, the weight of the metal bearing structure, the staff employed, the distance from the company, any contact with adjacent construction, the estimated duration and budget of the project. One critical factor was to ensure that the sample is as representative as possible. From the whole set of available data, special attention was provided to quantitative variables. The number and type of variables selected were defined by correlation analysis. Those variables that influenced the final cost were prioritized based on the degree of correlation. In this way, the input database was created to implement artificial neural networks.

The next stage included a series of tests to identify the most effective combination of input variables leading to a more accurate forecast of the actual cost. The main evaluation criterion for the accuracy of the prediction was theSum of Squares Error and Relative Error for the Training and Testing samples, which calculate the difference between the actual result and the one predicted by the artificial neural network. Given the combination of variables, a series oftests followed based on various design options of the artificial neural networks, in an attempt to optimize the prediction.

Training of the ANN was based on the collection of data from 20 different projects. These specific projects were carried out by a single construction company, which is currently based in the city of Thessaloniki, Greece. The figures below (Figures 1-10) show some statistics regarding the projects in relation to the input variables used.

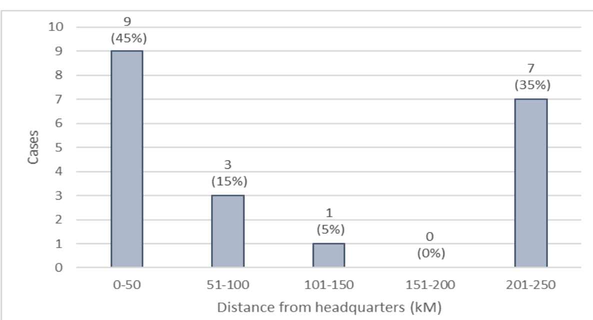

Fig. 47. Number of cases in relation to distance from enterprise headquarters

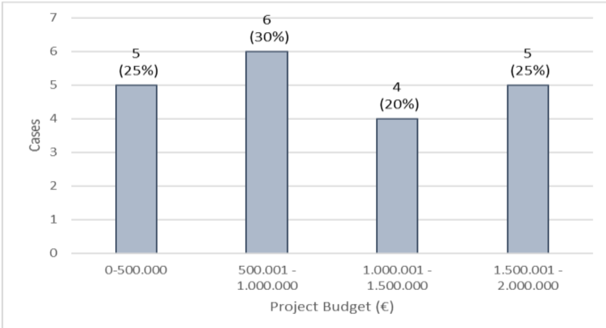

Fig. 48. Number of cases in relation to project budget

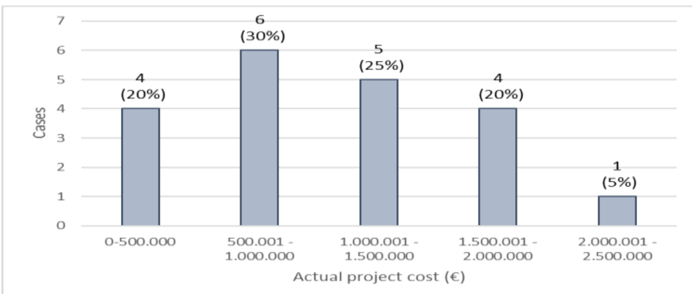

Fig. 49. Number of cases in relation to actual project cost

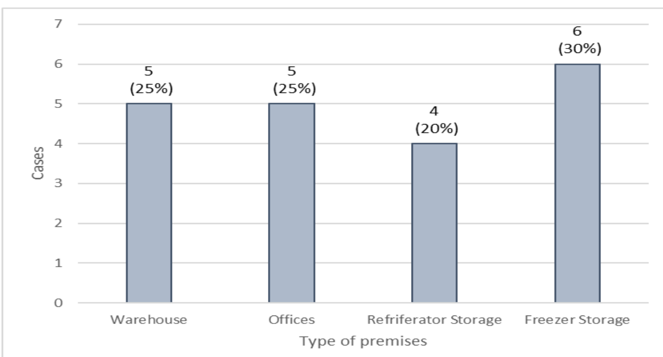

Fig. 4. Number of cases in relation to type of premises

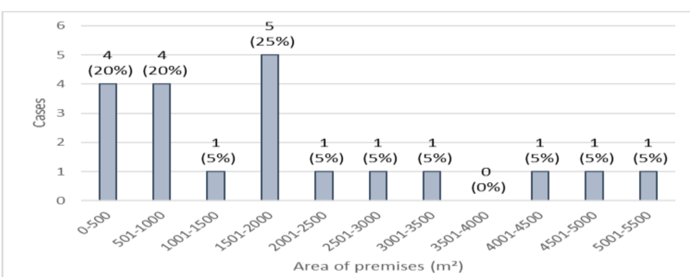

Fig. 5. Number of cases in relation to area of premises

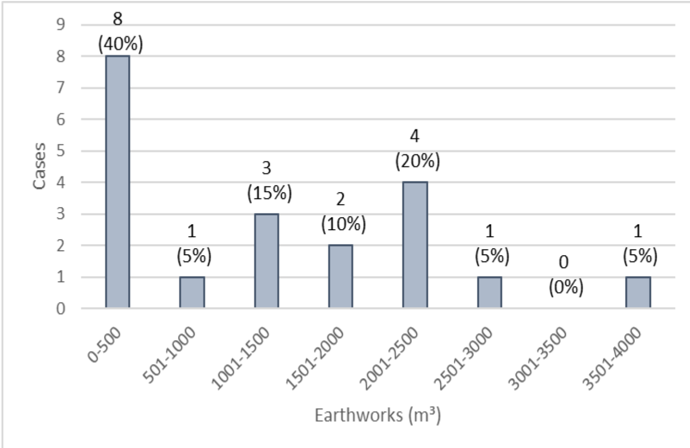

Fig. 6. Number of cases in relation to earthworks

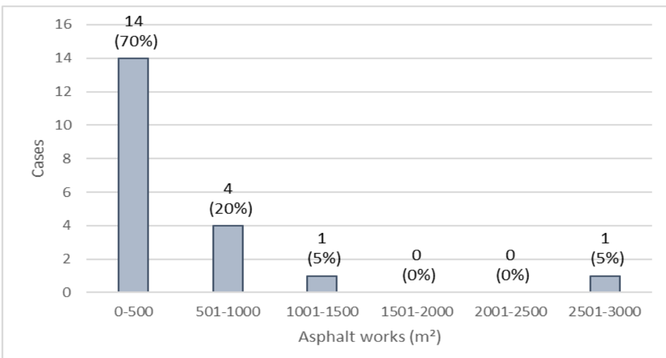

Fig. 7. Number of cases in relation to asphalt works

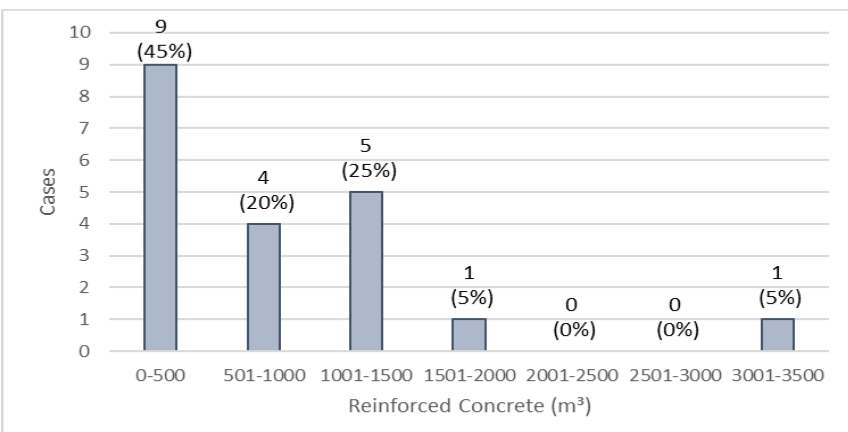

Fig. 8. Number of cases in relation to reinforced concrete

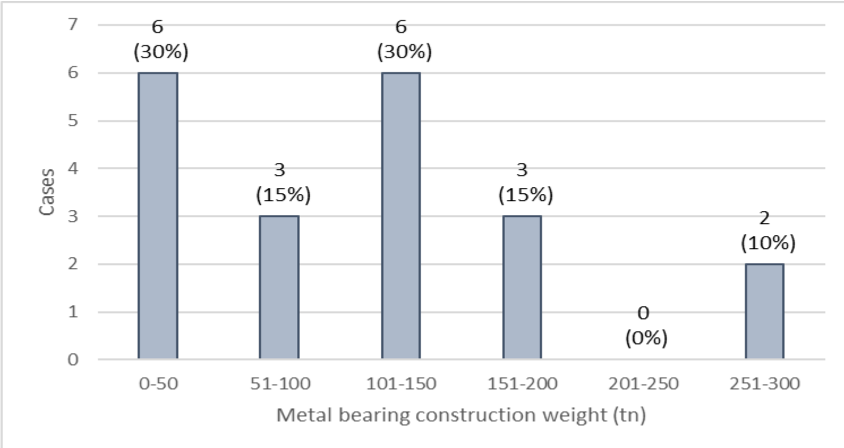

Fig. 9. Number of cases in relation to metal bearing construction weight

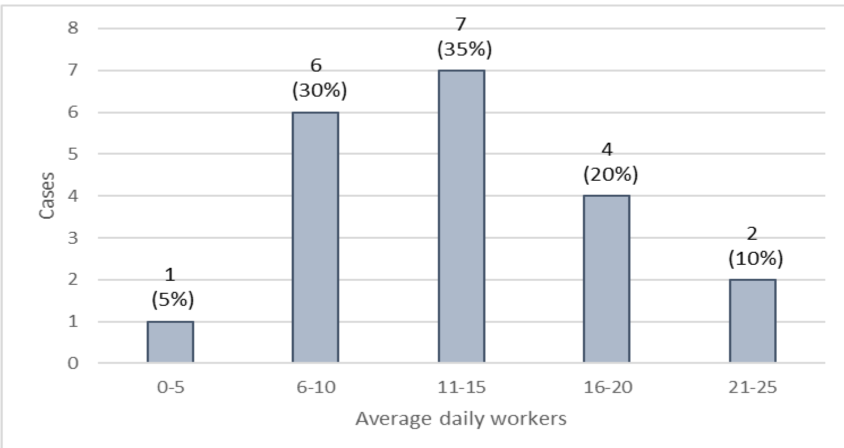

Fig. 50. Number of cases in relation to average daily workers

3. Results

3.1 Correlation Analysis

The correlation between two quantitative variables X and Y can be determined numerically using the correlation coefficient Pearson. The correlation coefficient Pearson r has no units of measurement and takes values in the interval from -1 to +1. Values close to one, positive or negative, are interpreted as almost perfect or very strong correlation, while values close to 0.5 are interpreted as moderate correlation. Values close to zero present a weak or absence of association (Field, 2009).

The following figure 11 presents the results from the correlation analysis, regarding cost. For an existence of correlation between two variables, the significance index Sig. (1- tailed) must be less than 0.05, while the hierarchy of the variables, which are related, is based on the Correlation Coefficient. Variables that show such a small significance index ($p < 0.05$) are shown in yellow, while if the value is even smaller ($p<0.01$) it is represented in green in the following Figure 11.

Actual Cost (€)		
	Pearson Correlation	Sig. (1-tailed)
Distance from Headquarters (km)	-0,338	0,100
Project Budget (€)	,995**	7,95E-16
Initial Project Duration (days)	,698**	0,001
Area of Premises (m^2)	,653**	0,003

Earthworks (m^3)	,543*	0,015
Asphalt Works (m^2)	-0,041	0,439
Reinforced Concrete (m^3)	,829**	3,57E-05
Metal Construction Bearing Weight (kg)	,723**	0,001
Average Number of Daily Workers	,850**	1,51E-05
Number of Different Personnel Disciplines	,657**	0,003

Fig. 11. Results of correlation analysis of quantitative variables with the Pearson correlation coefficient for actual cost

3.2 Application of Artificial Neural Networks

This section will present the results of the application of neural networks to predict the cost of the 20 industrial projects. In the effort to optimize the predictive capacity of the models, the results from the correlation analysis were used. Thus, various ANN's were constructed, with significant variations in the structure and the introduction of input variables. Hundreds of models were built with the help of the IBM SPSS 27 program using MLP (Multi-Layer Perceptron) which yielded better results than the corresponding RBF (Radial Basis Function). Both models presented in the current study are MLP. The first ANN for predicting actual cost and its parameters is detailed in Table 1 below. All available input variables have been used, regardless of correlation, in the order in which they are presented. The hidden level is divided into 8 units (neurons), while 70% of the sample is used for mini batch training and 30% for testing. Independent variables include: Type of premises, Contact with neighboring construction, Distance from headquarters (km), Project Budget (€), Predicted duration (days), Area of premises (m^2), Earthworks (m^3), Asphalt works (m^2), Reinforced concrete (m^3), Metal bearing construction weight (tn), Average daily workers, and number of different used disciplines per project. Details of the model regarding the hidden layer are the following:

- Number of Hidden Layers: 1
- Number of Units in Hidden Layer: 18
- Activation Function: Hyperbolic tangent

The output layer is the following:

- Dependent Variables: Actual Cost (€)
- Number of Units:1
- Activation Function: Identity
- Error Function: Sum of Squares

The deviation errors that occurred during training and testing are the following:

- Training Sum of Squares Error: 0,068
- Training Relative Error: 0,009
- Testing Sum of Squares Error: 0,148
- Testing Relative Error: 0,177

Figure 12 below sets out the diagrammatic representation of the actual and predicted cost for each of the 20 sample projects under consideration.

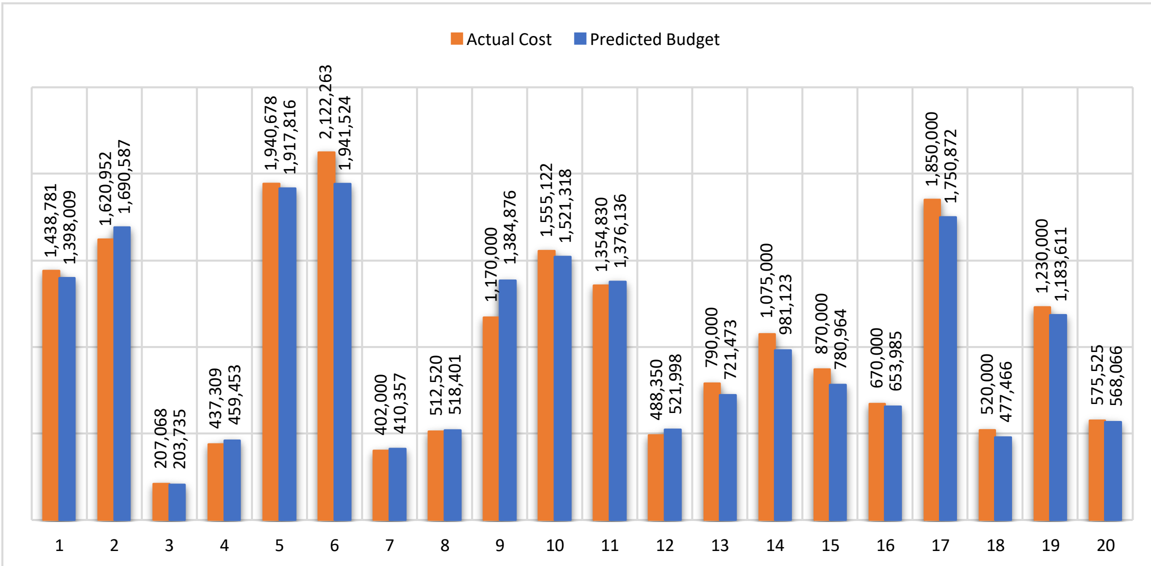

Fig. 12. Actual and predicted project cost according to the first forecasting model

Then follows the 2nd ANN for predicting actual cost. In comparison to the first model, the variable of asphalt works has been subtracted from the input variables, as correlation analysis shows that it does not play a significant role in predicting cost. The hidden level is divided into 7 units (neurons), while 70% of the sample is used for mini batch training and 30% for testing. The structure and variables of the second cost forecasting model include: Type of premises, Contact with neighboring construction, Distance from headquarters (km), Project Budget (€), Predicted duration (days), Area of premises (m^2), Earthworks (m^3), Reinforced concrete (m^3), Metal construction bearing weight (tn) and finally Average number of daily workers. The structure of the hidden layer is the following:

- Number of Hidden Layers:1
- Number of Units in Hidden Layer: 7
- Hidden Layer Activation Function: Hyperbolic tangent

The Output Layer includes:

- Dependent Variable: Actual Cost (€)
- Number of Units: 1
- Activation Function: Identity
- Error Function: Sum of Squares

The deviation errors for the second prediction model that occurred during training and testing are the following:

- Training Sum of Squares Error: 0,026
- Training Relative Error: 0,003
- Testing Sum of Squares Error: 0,011
- Testing Relative Error: 0,013

Figure 13 below sets out the diagrammatic representation of the actual and projected costs by the network for each of the 20 sample projects under consideration.

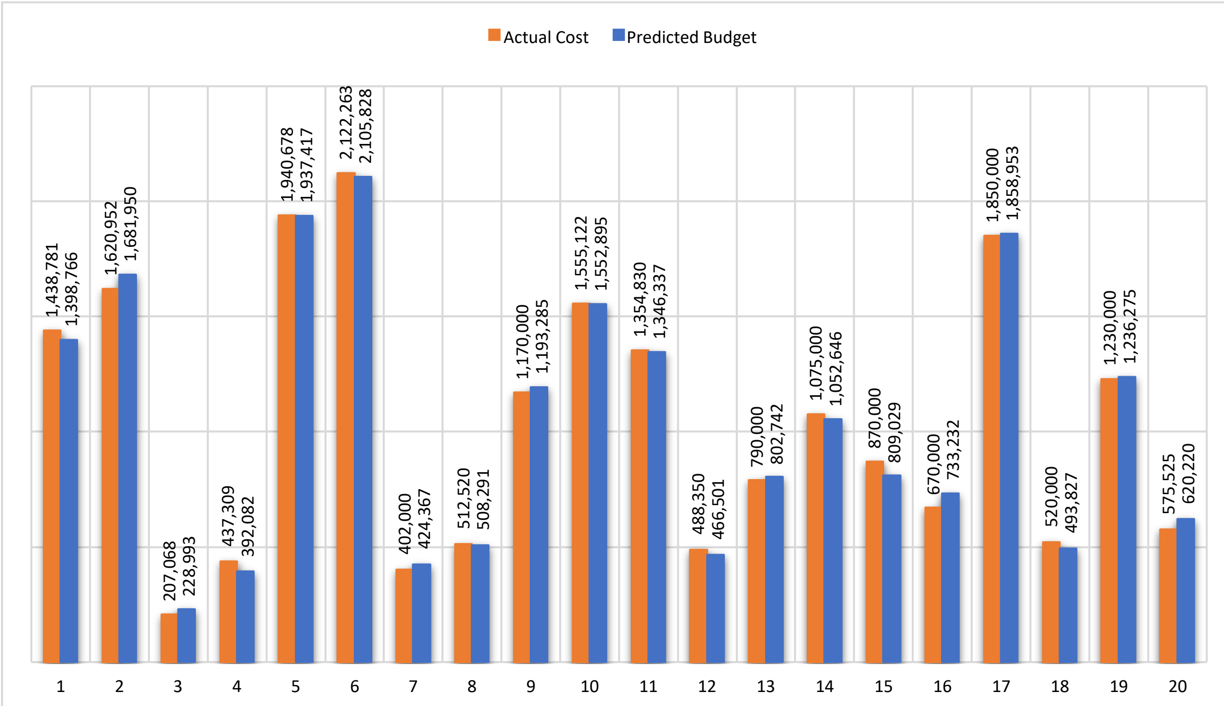

Fig. 13. Actual and predicted project costs according to the second forecasting model

5. Conclusions

In the current research, an attempt was made to predict the final cost of twenty industry-related construction projects, using neural networks. The results obtained showed that the neural network tool can also be applied to industrial projects, regardless of the type of variables used as input data. Although the number of projects was limited, the results were quite satisfactory.

The developed models showed sufficient accuracy based on the available data, and their estimates had errors with small differences between them. The second MLP model proved to be more accurate for cost forecasting, which did not include the quantity of "asphalt works" in the input variables and showed a total of 0.011 error and a relative error of 0.013. Also, a significant effect of categorical variables was observed which is particularly encouraging, as these variables are essentially the only way to distinguish the operation of installations. For neural network models, it was observed that the MLP method yielded better results than the Radial Basis Function model. It was also interesting that correlation analysis led to models with greater accuracy. Initially, all available input variables were used, and then taking into consideration the correlation analysis of variables, models with fewer variables, but with a greater impact on the output variable, were created. This resulted in greater accuracy of the produced models.

The sample size was an important parameter towards drawing more accurate conclusions. All the variables and their respective values were recorded with absolute reliability. Almost all the involved projects were managed by the authors. Also, an important limitation presented was the availability of options provided to the user by the software "IBM SPSS Statistics 27". With the use of the method "Multilayer Perceptron"(MLP) the options are comparatively more than the ones available within the "Radial Basis Function"(RBF) method. However, some options could be left to the user's discretion. Specifically, there is the possibility of selecting up to a maximum of two hidden layers, as well as specific activation functions and optimization algorithms. Also, the architecture of the network was clearly defined with simple feeding and learning under supervision. These limitations arose from the nature of the software and limited experimentation towards finding the optimal architectural structure of the neural network. One of the most important problems, which arises during the implementation of neural networks, is the choice of the appropriate training algorithm, as well as the overtraining of the network. In addition, due to the nature of the networks, the relationships between the parameters used for modelling are not sufficiently explained, making it difficult to explain how the network learns. Subsequently, a major problem during the development of artificial neural network models was the

evaluation of their accuracy by the software based on the relevant error during training, which substantially influence the decisions made by both the software and the user.
The result of the forecast of the cost for industrial projects proved to be quite promising. The key and main element that should be considered at a later stage is the training of the model with a larger database in order to evaluate its effectiveness. Also, the wider environment of the projects should be considered, keeping in mind that the current data concerns the methodology and the production rates of a particular construction company. Another interesting approach to the problem would be to obtain more data during the progress of the execution of the project, in order to give more information about each input in the neural network and therefore to make a better categorization of the data. Of course, since the complexity of the network and neurons would increase at the input level, care should be taken to gather a much larger sample and produce more extensive database to train the ANN model, otherwise problems of under-training could occur in the network.
An additional proposal for future research is the element of the initial definition of the values of weights of synapses between neurons in the neural network. In the current software, this process was done automatically, but initial values could be assigned to the weights through some method of estimating the importance of each input, such as the method of hierarchical decision analysis or the tree decision method. A different neural network architecture with more hidden layers could also be tested, but this should be done in a programming environment. In addition, in terms of experimenting with the structure, a network with feedback could be tested, which again makes its structure more complex and perhaps more efficient, with proper training. To this end, it is recommended to use more flexible software environments (e.g., MATLAB). Finally, the same methodological approach could be followed to investigate the accuracy of forecasts in different types of construction projects, and a comparison could be made to examine whether the model structure and the use of these options produces better results.

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