



Using Artificial Neural Networks in assessing the cost of Construction Projects

Otsokov Kamil Alievich¹

¹National Research Moscow State University of Civil Engineering (NRU MGSU), Russia

ostokovkam@mail.ru

ABSTRACT

The sphere of construction and architecture primarily sets itself the task of creating a functional and interoperable space that will meet the primary and daily needs of a person. The evolution of urban planning principles has led to the need to increase the degree of urbanization, density of buildings, expansion of functional links between public and residential elements of the urban environment, to the formation of multifunctional residential complexes with an "open" service system. A multifunctional residential complex is a modern form of organization of the city's residential environment, in which the needs of each personal housing, work, recreation and communication are most fully realized. Demand creates supply. Gradually, there is a change of concept in the organization of construction. Investors and developers first think through the organization of the multifunctional residential complex under construction, as the quality of housing and the possibility of obtaining various services directly in the area of residence are valued very highly.

One of the most important factors for construction companies is cost. Any feasibility study for any investment (project) requires an accurate cost estimate in order to make the right decision about the future fate of the project: move forward, or cancel the investment. In addition, cost estimation is a very important tool for managing construction projects. For example, it provides founders with a perfect image for the projected cash flow (cash flow) over the entire life cycle of the project. Thus, improving the methods of estimating the cost of the will contribute to more effective control over time and costs in construction. The reliability and reliability of these estimates is significantly affected by a number of uncertain but predictable factors. The main function of cost estimation is to create a reliable forecast of the cost of construction. However, the projected cost depends on the customer's needs and the available information and data.

Key words: Neural network, buildings, estimate costs, construction.

1. INTRODUCTION

The creation of multifunctional complexes is due to its following advantages over highly specialized centers [1-7]:

- efficient use of the land plot and saving of resources (in particular energy resources);
- reducing the unit cost of creating an item due to its scale;
- flexible repurposing possible with increased competition in the market;
- the target audience has several reasons for visiting the site;

- high investment attractiveness of the project, due to the reduction of risks due to the diversification of investments (investment in different types of real estate).

Many studies have been conducted on the use of neural networks in construction projects [8-10]. For example, the study focuses on developing a model for estimating the cost of construction projects at an early stage in the Gaza region. The data sets were collected from 71 projects [11-19]. The artificial neural network model that was developed had a hidden layer and seven neurons. The results obtained during the simulation and after the training showed that the neural network was able to reasonably anticipate the cost of buildings at an early stage, using basic project information and without the need for more detailed development. After analyzing the sensitivity, we saw that there were many effective factors, such as the floor area of the first floor, the number of foundations and the number of elevators in buildings, that affect early estimates of the cost of a building [6].

Another example of research is devoted to the development of a model using an artificial neural network, which can provide for the total cost of construction projects in the country of the Philippines. Data sets from 30 completed projects were collected and randomly divided into three groups: 20% for performance testing, 60% for training, and 20% for network generalization. Six parameters were selected as input parameters. These variables were first introduced into the structure of an artificial neural network, and the simulation was performed using MATLAB. Then a better model was developed to estimate the total structural cost. It consisted of 7 hidden layer nodes, 1 source node, and 6 variables as input. The model of artificial neural network was also developed and provided for the full structural cost of buildings with sufficient preparation and results of stage b testing [7].

Despite the high performance of neural networks in previous studies, the process of developing and implementing neural networks for parametric cost estimation has a number of problems related to the

network itself [20]. First, designing a network architecture and setting its parameters is not a simple approach; it requires some trial and error processes. Second, learning algorithms such as reverse propagation require optimization of network training in order to achieve adequate generalization, otherwise the memory capacity will be used by the network to remember the actual results. This problem can be easily avoided at the learning stage by prohibiting a network error from being zero, because a zero network error means that the network remembers.

2. MATERIALS AND METHODS

Parametric estimation is a method that uses a statistical relationship between historical data and other variables to value the resources of a planned operation. Using this method, you can get a more accurate estimate of the cost, because this approach requires less detail compared to other methodologies. The level of accuracy of the estimate depends on the complexity, the amount of resources allocated for such work, and the cost data embedded in the model. For example: in order to get an estimate of the cost, you need to multiply the planned amount of work by the cost of one unit in the past [4].

Developing a new model for estimating parametric costs is quite a complex process, so it needs to be simplified by creating a course of action that covers whole parts of this process:

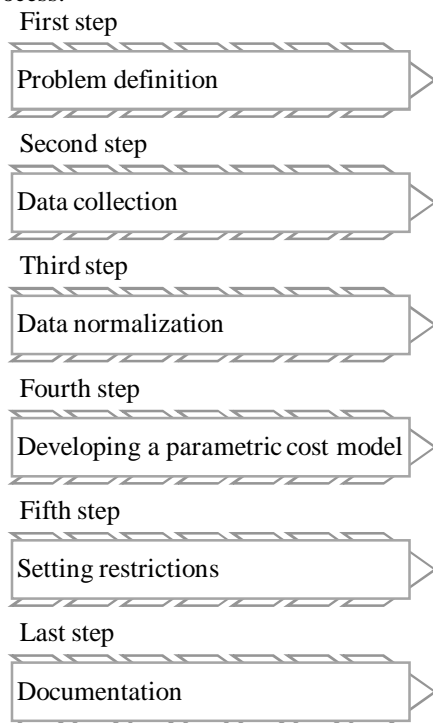


Figure 1: procedure of parametric cost estimating

Figure 1 shows the procedure of parametric cost estimating.

The first step is to identify the problem. Defining a problem is the first step in any given scientific method.

The second step is data collection. Parametric estimation requires a large database where historical records are extremely important. Design and engineering parameters that control parametric cost estimates are developed from

the peripheral cost is to database. Data collection can be considered as the most important stage. Without sufficient relevant data, parametric estimation cannot be successfully implemented.

The third step is data normalization. This process ensures that every single database entry is located in the same database. As a rule, in a construction project, the cost data for each project must be adjusted to differ in time and location. This step is important and must be completed before further data analysis can be performed [24].

The third step is the development of a parametric model of cost estimation. It provides for determining the relationships of variables used in the model, and inferring the cost estimation relationships. Cost estimation ratios are mathematical models or graphs that estimate the cost. The basis for selecting parameters to use in the model should be more than just statistical confidence, but the inclusion of parameters should also be based on logical and theoretical reasoning.

The fifth step of the parametric estimation procedure is to establish model constraints. The model is usually designed with a limited data set, so it only applies to the ranges of variables used in the model [21].

The last, sixth stage is the documentation processing model development [22]. The assumptions and limitations of the model must be properly formulated to facilitate successful implementation of the model. Notes should also be written for any uncertainty in the data and its estimation. The information and meaning of terms used in data collection and model development should be documented along with all calculation methods [9].

An artificial neural network is a mathematical model, as well as its software or hardware implementation, based on the principle of organization and functioning of biological neural networks - networks of nerve cells of a living organism. This concept arose when studying the processes that occur in the brain of a living organism, and when trying to model these processes [23].

Neural network is based on a set of interconnected nodes, which are called artificial neurons (similar to biological neurons in the brain of living creatures). Each connection between artificial neurons can transmit a signal from one to the other [1].

An artificial neural network usually consists of three layers: an input bus with input neurons, a hidden layer with hidden neurons, and an output layer with output neurons-a perceptron

Frank Rosenblatt, proposed by him in 1957 (Figure 1).

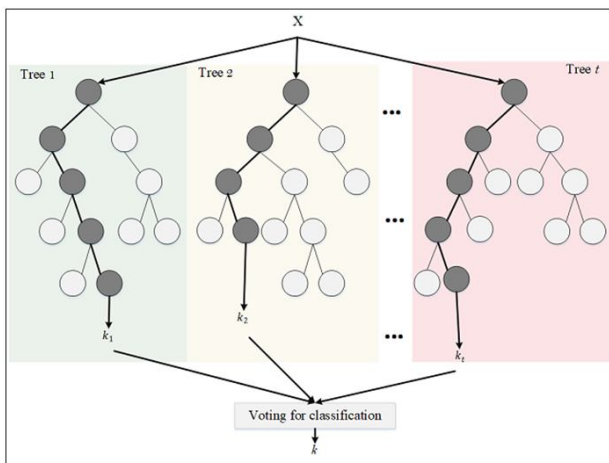


Figure 2: Schematic representation of the technique of random decision forests

Figure 2 shows the schematic representation of the technique of random decision forests in neural network. Each input layer neuron is connected to each neuron in the hidden layer, and in turn, each hidden layer neuron is connected to each output layer neuron. The one of the hidden layers and the number of neurons in each hidden layer can be one or more. The number of network neurons, hidden neurons, and output neurons is the network architecture [6].

Combining a large number of neurons into a single network allows you to solve quite complex problems. Knowledge enters the neural network from the environment and is used in the learning process. For the accumulation of knowledge, connections between neurons are used, which are called synaptic scales [27].

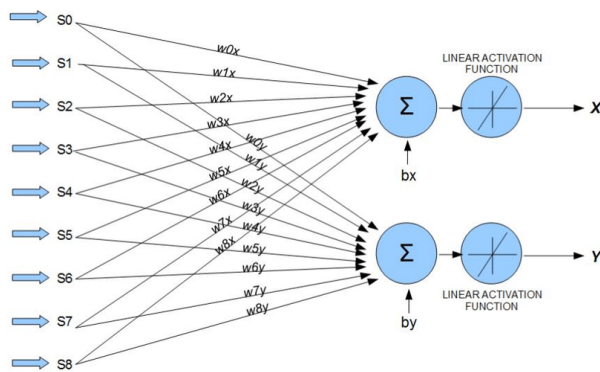


Figure 3: Diagram of the neuron / Neural circuit

Figure 3 shows us the diagram of the neuron with active signals.

Signals X_i arrive at the input of the neuron, are multiplied by the corresponding weight coefficients W_i , after which their sum S_i is obtained with the help of an adder. The summation result is sent to a nonlinear Converter that implements some nonlinear function called the activation function for the neuron transfer function: the result of its action is sent to the output of the neuron – Y [3].

By its organization and function, an artificial neural

network with multiple inputs and outputs performs some transformation of input stimuli - sensory information about the external world-into output control signals. The number of converted stimuli n is equal to the number of network inputs, and the number of output signals corresponds to the number of outputs m . A collection of all possible input vectors of dimension n forms a vector space X . Similarly, the output vectors also form an unsigned space, which will be denoted by Y . Now the neural network can be represented as a certain multidimensional function $F: X \rightarrow Y$, whose argument belongs to the signed input space, and whose value belongs to the output signed space [25].

For an arbitrary value of synaptic weights of neurons in the network, the function that is implemented by the network is also arbitrary. To get the desired function, you need a specific selection of weights. The ordered set of all weights of all neurons can be represented as a vector W . The set of all such vectors also forms a vector space, which is called the I state space or the configuration (phase) space W . The term "phase space" comes from the statistical physics of systems of many particles, where it is understood as a set of coordinates and pulses of all the particles that make up the system.

Setting a vector in the configuration space completely determines all synaptic weights and, thus, the network state. The state at which the neural network performs the required function is called the trained state of the W^* network. For a given function, the trained state may not exist, or it may not be the only one. Training tasks are now formally equivalent to constructing a transition process in the configuration space from some arbitrary state W^0 to a trained state.

This function is uniquely described by specifying the correspondence of each vector of the feature process X to some vector from the space XY . In many practical cases, the values of the necessary functions for given argument values are obtained from experiments or observations, and therefore are known only for a limited set of vectors. In addition, known function values may contain errors, and individual data may even partially contradict each other. For these reasons, a neural network is usually assigned the task of approximating the function with the available examples.

The example and correspondence between vectors available to the researcher, or the most representative data specially selected from all the examples, is called a training sample. The training sample is usually determined by specifying pairs of vectors, and in each pair, one vector corresponds to the stimulus, and the other one corresponds to the required response. Training of a neural network consists in bringing all the stimulus vectors from the training sample to the desired responses by selecting the weights of neurons.

The most common way to optimize a neural network is a post wait upon the procedure of selection of weights, which is called training. If this procedure is based on a

repeated sample of examples, it is called "learning with a teacher".

Let there be a neural network that performs the transformation $\mathbf{f}: \mathbf{X} \rightarrow \mathbf{Y}$ vectors \mathbf{X} from the feature space of inputs \mathbf{X} to the vectors \mathbf{Y} of the output space \mathbf{Y} . The network is in state \mathbf{W} from the state space \mathbf{W} . Let us then have a **training sample** $(\mathbf{X}^a, \mathbf{Y}^a)$, $a = 1 \dots p$. Consider the complete **error** \mathbf{E} that the network makes in state \mathbf{W} :

$$E = E(\mathbf{W}) = \sum_a \|F(\mathbf{X}^a; \mathbf{W}) - \mathbf{Y}^a\| = \sum_a \sum_i [F_i(\mathbf{X}^a; \mathbf{W}) - Y_i^a]^2$$

Note two properties of the complete error. First, error $\mathbf{E} = \mathbf{E}(\mathbf{W})$ is a state function \mathbf{W} defined on the state space. By definition, it takes nonnegative values. Secondly, in a certain trained state \mathbf{W}^* , in which the network makes no errors on the training sample, this function takes a null value. Here, the trained States are the minimum points of the entered function $\mathbf{E}(\mathbf{W})$.

Thus, the task of training a neural network is to find the minimum error function in the state space, and standard optimization theory methods can be used to solve it. This problem belongs to the class of multi-factor problems, so, for example, for a single-layer perceptron with \mathbf{N} inputs and \mathbf{M} outputs, we are talking about finding the minimum in $\mathbf{N} \times \mathbf{M}$ dimensional space [5].

The essence of all approaches to Neuroinformatics is the development of methods for creating (synthesizing) neural circuits that solve certain tasks. In this case, the neuron looks like a fairly simple device: something like an amplifier with a large number of inputs and one output. The difference between approaches and methods is in detail with the image in the neuron's operation and the image of the connections' operation. The main load on the performance of specific functions by processors falls on the architecture of the system, the details of which, in turn, are determined by micro-neural connections [2].

3. CONCLUSION

One of the main advantages of the Bayes algorithm is that the results are quite good when there is not much training data. The most important advantage of using support vector machines is that the results are usually better than those obtained using a simple Bayesian method. However, additional computing resources are required to use support vector machines.

Deep learning algorithms demonstrate greater accuracy and performance than classical approaches, but it is more difficult to implement such models. Recurrent neural networks, or RNNS, are popular for tasks where data order is important, when the network needs to figure out a pattern in the data sequence. RNNS are usually applied to problems such as natural processing, since data order matters when deciphering the meaning of a sentence. One of the main problems is collecting data for network training. Artificial neural networks are successfully used in solving numerous complex nonlinear problems related to forecasting, evaluation, decision making, optimization, systematization and selection in the fields of construction and its management. Artificial neural networks are

particularly effective for solving complex problems, such as cost estimation problems, where the relationship between variables cannot be distorted by simple mathematical relationships.

REFERENCES

1. **Early Stage Cost Estimation of Buildings Construction Projects using Artificial Neural Networks**. *Journal of Artificial Intelligence* 4 (1): 63-75, 2011, ISSN 1994 - 5450 I DOI: 10.3923/jai.2011.63.75 Department of Civil Engineering, The Islamic University of Gaza, P. O. Box 108, Palestine.
2. S. Ahmad, "**Optimum concrete mixture design using locally available ingredients**," *The Arabian Journal for Science and Engineering*, vol. 32, no. 1, pp. 27–33, 2007.
3. H. Binici, H. Kaplan, and S. Yilmaz, "**Influence of marble and limestone dusts as additives on some mechanical properties of concrete**," *Scientific Research & Essay*, vol. 2, no. 9, pp. 372–379, 2007.
4. O. Y. Marzouk, R. M. Dheilily, and M. Queneudec, "**Valorization of post-consumer waste plastic in cementitious concrete composites**," *Waste Management*, vol. 27, no. 2, pp. 310–318, 2007.
5. D. Lutskiy, T. Litvinova, I. Olejnik, I. Fialkovskiy. **Effect of anion composition on the extraction of cerium (Iii) and yttrium (Iii) by oleic acid** (2018) *ARN Journal of Engineering and Applied Sciences*, 13 (9), pp. 3152-3161.
6. D. Lutskiy, T. Litvinova, A. Ignatovich, I. Fialkovskiy. **Complex processing of phosphogypsum - A way of recycling dumps with reception of commodity production of wide application** (2018) *Journal of Ecological Engineering*, 19 (2), pp. 221-225.
7. O. Cheremisina; V. Sergeev; V. Alabusheva; A. Fedorov; A. Iliyana. **The Efficiency of Strontium-90 Desorption Using Iron (III) Solutions in the Decontamination Process of Radioactive Soils**. *Journal of Ecological Engineering* WOS:000428724900017. 2-s2.0-85042483092. 2018 (No. 2, V. 19, 2018. P 149-153.)
8. S. V. Klyuev, S.N. Bratanovskiy, S.V. Trukhanov, H.A. Manukyan. **Strengthening of concrete structures with composite based on carbon fiber** // *Journal of Computational and Theoretical Nanoscience*. 2019. V.16. №7. P. 2810 – 2814.
9. A. Kuzhaeva& I. Berlinskii. 2018. **Effects of oil pollution on the environment. In International Multidisciplinary Scientific GeoConference Surveying Geology and Mining Ecology Management, SGEM** (Vol. 18, pp. 313–320). <https://doi.org/10.5593/sgem2018/5.1/S20.041>
10. I. Berlinskii& I. Zhadovskiy. 2017. **Physico-chemical characteristics of cations of non-ferrous metals on ferromanganese nodules. In International Multidisciplinary Scientific GeoConference Surveying Geology and Mining Ecology Management, SGEM** (Vol. 17, pp. 943–948). <https://doi.org/10.5593/sgem2017/11/S04.120>

11. I. Berlinskii & A. Kuzhaeva. 2017. **The study of the mechanism of the oxidative desulphurization. In International Multidisciplinary Scientific GeoConference Surveying Geology and Mining Ecology Management, SGEM (Vol. 17, pp. 1001–1008).**
<https://doi.org/10.5593/sgem2017/51/S20.037>
12. O. Lobacheva & I. Berlinskii. 2017. **Er(III) solvent sublation from dilute aqueous solutions. In International Multidisciplinary Scientific GeoConference Surveying Geology and Mining Ecology Management, SGEM (Vol. 17, pp. 409–416).**
<https://doi.org/10.5593/sgem2017/51/S20.094>
13. I. Berlinskii & A. Kuzhaeva. 2016. **The study of calcium-silicate based adsorbents properties. In International Multidisciplinary Scientific GeoConference Surveying Geology and Mining Ecology Management, SGEM (Vol. 2, pp. 1229–1235).**
14. O. L. Lobacheva, I. V. Berlinskii & N. V. Dzhevaga. 2017. **Thermodynamics of complexation in an aqueous solution of Tb(III) nitrate at 298 K. Russian Journal of Physical Chemistry A, 91(1), 67–69.** <https://doi.org/10.1134/S0036024417010162>
15. O. Lobacheva & I. Berlinskii. 2016. **Solvent sublation of the TB (III) from aqueous solutions with sodium dodecyl sulfate.** International Journal of Applied Engineering Research, 11(9), 6350–6354.
16. O. Lobacheva & I. Berlinskii. 2016. **Ho(III) solvent sublation from dilute aqueous solutions by sodium dodecyl sulfate.** In International Multidisciplinary Scientific GeoConference Surveying Geology and Mining Ecology Management, SGEM (Vol. 2, pp. 1097–1102). <https://doi.org/10.5593/sgem2016B12>
17. N. K. Kondrasheva, A. M. Ereemeeva, K. S. Nelkenbaum, O. A. Baulin & O. A. Dubovikov. 2019. **Development of environmentally friendly diesel fuel, Petroleum Science and Technology, 37:12, 1478-1484, DOI: 10.1080/10916466.2019.1594285**
18. N.K. Kondrasheva, A.M. Ereemeeva & K.S. Nelkenbaum. 2018. **Development of domestic technologies of producing high quality clean diesel fuel. Izvestiyavysshikhuchebnykhzavedeniikhimiyakhi micheskayatekhnologiya, 61(9-10), 76-82.** <https://doi.org/10.6060/ivkkt.20186109-10.5651>
19. A. Semenyutina, I. Svintsov, A. Huzhahmetova & V. Semenyutina. (2018). **Regulation of increase of biodiversity of woody plants in protective forest plantings of the Volga region.** World Ecology Journal, 8(2), 46-59.
<https://doi.org/https://doi.org/10.25726/NM.2018.2.2.005>
20. A. Tereshkin. (2018). **Specificity of optimization of recreational potential Forest park (on the example of the green zone of Saratov).** World Ecology Journal, 8(2), 60-70.
<https://doi.org/https://doi.org/10.25726/NM.2018.2.2.006>
21. M. Belitskaya. (2018). **Ecologically adaptive receptors control the number of pests in the ecosystems of transformed at the forest reclamation.** World Ecology Journal, 8(2), 1-10.
<https://doi.org/https://doi.org/10.25726/NM.2018.2.2.001>
22. I. Lovanov. (2018). **Solution of the problem of the theoretical profile of non-dimensional speed on the thickness of the boundary layer at the turbulent flow in the boundary layer based on the solution of the differential equation of Abel of the second generation with the app.** World Ecology Journal, 8(1), 43-51.
<https://doi.org/https://doi.org/10.25726/NM.2018.1.1.004>
23. I. Berlinskii & I. Zhadovskiy. (2017). **Physico-chemical characteristics of cations of non-ferrous metals on ferromanganese nodules. In International Multidisciplinary Scientific GeoConference Surveying Geology and Mining Ecology Management, SGEM (Vol. 17, pp. 943–948).** <https://doi.org/10.5593/sgem2017/11/S04.120>
24. Vitalii, S., Oleh, V., Oksana, T., Olha, P., German, S., Maksym, T., ... Marianna, K. (2019). **Influence of the composite materials nonlinear properties with radioisotope inclusions on reflected radiation.** International Journal of Advanced Trends in Computer Science and Engineering, 8(6), 2716–2720.
<https://doi.org/10.30534/ijatcse/2019/05862019>
25. Wang, G., & Hwa, T. H. (2019). **Designing business model canvas for motorcycle rental based mobile application (Case study at PT XYZ).** International Journal of Advanced Trends in Computer Science and Engineering, 8(5), 1841–1855.
<https://doi.org/10.30534/ijatcse/2019/06852019>
26. A.V. Shashkova, I.A. Rakitskaya & E.Y. Pavlov. (2017). **Emergence and activity of legal entities in Russia in the pre-revolutionary period (comparative analysis).** *Bylye Gody*, 46(4), 1333–1344. <https://doi.org/10.13187/bg.2017.4.1333>
27. R.A. Abramov. (2016). **Regional economic policy based on industrial sector clustering in the context of sustainable development.** *Research Journal of Pharmaceutical, Biological and Chemical Sciences*, 7(2), 2100–2106.