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Investigating the Selection of the Optimal Financing Method in Housing Construction Using Artificial Neural Networks

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Abstract

Optimization remains one of the most critical issues in civil engineering studies. In this case, the study focused on the development of three types of Artificial Neural Networks (ANNs), which included the Multilayer Perceptron (MLP), Neuro-Fuzzy (NF), and Radial Basis Function (RBF). The four input parameters for each model have been used while the output parameter remained the predicted final profit. For the development of MLP models, the use of one or two hidden layers with varying number of neurons was considered to identify the best structure of MLP network. The most efficient NF network was obtained by modeling using various membership functions, depending on error indices. Because ANNs function in a closed loop and the impact of input parameters on output cannot be indicated in any form, an uncertainty analysis was performed to find out the absolute derivatives of the output parameter with regard to the four input parameters. Following this, the relative derivatives of the output regarding each of the input parameters were analyzed. It was found that the MLP neural network was the best performing model among all of the models studied. In addition, the sensitivity analysis found that pre-sale financing method was the most significant input parameter.

Keywords: Housing finance, Artificial neural networks, Optimization, Sensitivity analysis.

1 | Introduction

Construction is one of the most important industries in the world economy and acts as a fundamental element in infrastructure development, economic growth, and provision of investment opportunities. In all types of construction, house construction stands out because of its capital-intensive nature and its long periods of execution together with high sensitivity to the economic environment. These are reasons why such

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construction projects continuously experience many financial challenges in terms of managing capital and raising enough money for their execution. Choosing the right method of financing can be considered as one of the most crucial decision-making processes in construction projects since it influences all aspects of the construction process.

The difficulty in making financial decisions in residential projects stems from the impact of many factors on these decisions at once. Market fluctuations, changes in construction prices, funding availability, interest rates, and investment climate, among other things, contribute to the intricacy and multiplicity of factors involved in making decisions regarding the choice of funding sources. In this case, conventional decision-making procedures and linear statistical analysis become inadequate for dealing with interdependencies among variables.

The evolution of the field of information technology and the invention of artificial intelligence-based techniques over the last several decades have created new possibilities for data analysis within the construction sector. Among the different techniques of artificial intelligence, the use of Artificial Neural Networks (ANNs) as an essential branch of machine learning has gained a lot of attention, especially because of its capacity to discover the hidden patterns, represent the non-linear relationship between input/output parameters, and predict the behavior of complex models [1–4].

The introduction of neural networks to civil engineering and construction management dates back to the early 1990s, after which their use gradually spread to cost estimating, productivity forecasting, resources management, performance assessment, risk management, and decision-making systems [5–7]. Over the past few years, considerable attention has been paid to using ANNs for cost prediction in construction, data analysis, and optimizing decision-making processes [8–11]. Scientometric analyses conducted over recent years have shown that ANNs still continue to be one of the most popular research topics in construction management [12], [13].

While many research efforts have been carried out to apply neural networks in various civil engineering issues, only a few of these studies have focused on applying neural networks in cost estimation, prediction of performance in civil engineering projects, and resource management. However, much less research has been done in using this type of intelligent approach in choosing appropriate financing schemes for construction projects. As the choice of financing scheme determines how successful a construction project will be from a business point of view, an intelligent model capable of recognizing the right financing option will certainly help reduce the risk factor associated with investments in these projects. In light of the above observations, this paper attempts to test the capability of ANNs in selecting appropriate financing schemes for housing construction projects.

2 | Literature Review

The use of ANNs has become a widespread practice since the 1980s as one of the most significant artificial intelligence tools that can be applied in engineering applications. The creation of neural learning algorithms and backpropagation techniques proposed by Rumelhart et al. [4] created the basis for application of the mentioned technologies in order to resolve complex engineering tasks. In turn, Adeli et al. [1], [2] pointed at the importance of applying machine learning and neural networks in engineering applications due to their capacity to model nonlinearity and contribute to engineering decision making. Furthermore, Garrett [14] and Moselhi et al. [6] introduced neural networks as effective means for solving complex problems in civil engineering and construction management.

Among the significant applications of neural networks within the construction sector, one should highlight project cost estimation and forecasting. Boussabaine and Kaka [15] developed the neural network model of construction project cost flow forecasting capable of modeling complicated financial interrelations with an acceptable degree of accuracy. ElSawy et al. [16] used neural networks to predict construction site overhead cost and found their accuracy higher compared to traditional methods. Hegazy and Ayed [17] suggested a neural network model of parametric cost estimation of highway projects capable of predicting costs with a high level of reliability. The same conclusion regarding the high effectiveness of neural networks in the field of project cost estimation was made by Wilmot and Mei [18], Arafa and Alqedra [8], and Fernando et al. [3].

However, due to development in digital technologies, current literature has concentrated more on the integration of neural networks with other types of intelligent systems. Zhao et al. [9] incorporated genetic algorithms into BIM to develop a construction cost prediction model, which had better performance compared to previous methods. On their part, Matel et al. [10] and Car-Pusic et al. [11] used neural networks to estimate costs related to engineering services and project costs in the early stages of planning, and the results were very satisfying.

Other than cost estimation, neural networks have also been widely applied in project management and decision support systems. Cheung et al. [19] applied neural networks to categorize satisfaction ratings in the process of resolving disputes in projects and proved that neural networks are effective in managerial decision analysis. In other researches, Cheung et al. [20] have built a neural-network model for forecasting the performance of projects, and found out that managerial and operational factors greatly impact on the success of projects. Golpayegani et al. [21] have used modular neural networks in developing work breakdown structure designs, and found out that neural networks are useful in project planning and management.

Neural networks have also been extensively used for forecasting productivity and managing resources. For example, Chao and Skibniewski [22] used neural networks to forecast construction productivity, which gave them satisfactory results. Hua [23] used ANNs as an alternative approach to regression models for predicting residential construction demand, where he showed that neural networks were more accurate. On the other hand, Mirahadi and Zayed [24] combined neural networks with fuzzy logic to develop a model for forecasting productivity that would be able to cope with uncertainty. Finally, Savin et al. [25] used neural networks for leveling and allocating resources.

The role of neural networks in construction management has been validated through recent literature review studies and scientometric analyses. Boussabaine [5] presented one of the pioneering studies which reviewed applications of neural networks in construction management. Kulkarni et al. [7] further showed that the major applications of neural networks in construction management are cost estimating, risk assessment, scheduling, and managerial decisions making. In the latest developments in this field, Xu et al. [12] and Kaushik et al. [13] conducted a scientometric analysis on neural networks in construction projects. They found significant increase in research on ANNs in the construction industry.

Despite the wide usage of neural networks in cost estimation, forecasting production effectiveness, resources management, and project performance assessment, little attention has been paid to the application of neural networks in financing method selection and evaluation in the field of housing construction. As a result, it is evident that financing choices remain one of the key strategic variables influencing project profitability and risks as well as the general success of the project under discussion. The development of neural network models to examine and select the best options for financing thus presents an important avenue of research.

3 | Research Methodology

In this study, the data gathered from 100 housing constructions carried out through various financing approaches were used. This project was carried out in various places including Tehran and Alborz provinces, and its structural and financial features can be related to the parameters provided in *Table 1*.

In order to choose the variables affecting the housing project financing, four variables associated with the financing approach were selected as the input parameters of the models that included the bank loan (V), presale financing (P), initial personal capital (S), and joint venture financing (M). The net profit value (B) was chosen as the output parameter. A sample of the input data applied in training ANN models can be seen in *Table 1*.

Also, an example of the sample project can be seen in *Fig. 1*.

Table 1. Sample input database (values in Billion Toman).

Company	Input Parameters				Output Parameter
	M	S	P	V	B
Estaban	2.56	4.51	4.1	7.64	1.176
Estaban	3.13	5.50	5.0	8.60	1.323
Estaban	3.88	6.82	6.2	8.33	1.281
Estaban	2.81	4.95	4.5	8.19	1.260
Estaban	2.69	4.73	4.3	7.92	1.218
Estaban	3.19	5.61	5.1	7.78	1.197
Mehraz Sazeh	2.81	4.95	4.5	6.83	1.050
Mehraz Sazeh	3.19	5.61	5.1	6.55	1.008
Mehraz Sazeh	3.94	6.93	6.3	8.87	1.365
Mehraz Sazeh	4.44	7.81	7.1	9.28	1.428
Mehraz Sazeh	4.44	7.81	7.1	9.01	1.386
Mehraz Sazeh	4.50	7.92	7.2	9.42	1.449
Mehraz Sazeh	3.88	6.82	6.2	9.56	1.470
Mehraz Sazeh	3.19	5.61	5.1	9.15	1.407
Alborz Designers	8.63	15.18	13.8	20.75	3.192
Alborz Designers	2.69	4.73	4.3	7.51	1.155
Alborz Designers	4.88	8.58	7.8	11.06	1.701
Alborz Designers	6.31	11.11	10.1	12.56	1.932
Alborz Designers	3.94	6.93	6.3	8.87	1.365
Alborz Designers	4.50	7.92	7.2	9.28	1.428

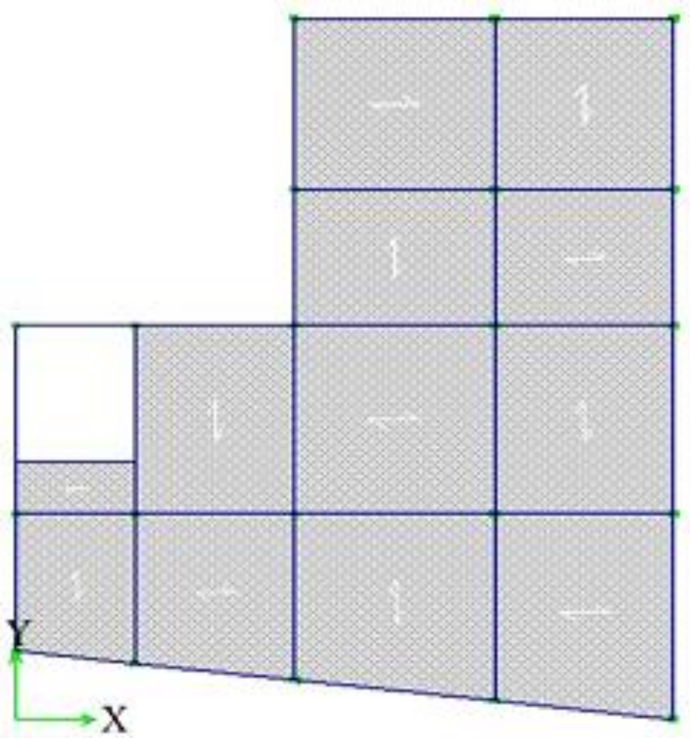


Fig. 1. Plan and layout of a sample of the investigated structures.

3.1 | Artificial Neural Network Architecture

3.1.1 | Input variables

Taking into account the elements affecting the financing of the projects, four parameters related to the financing process were chosen as the input parameters of the neural network model. They are bank financing (V), pre-sale financing (P), initial investment by the owner (S), and joint venture financing (M). The last parameter is the ultimate net profit (B).

In choosing the input variables, consideration was not only based on the function of those variables in the funding of the residential buildings but also on their strong effect on the profitability of the entire project. Consequently, variables that had the highest impact on the performance of the residential building projects were selected as model inputs. At this point in the study, neural network models were created using four input variables. These variables were extracted based on the features of the residential building projects.

In the end, the total net profit realized from every single project served as the only output parameter of the modeling process. The reason for this is that this parameter served as the main indicator when assessing the effectiveness of various financing strategies.

Ranges of variation for the input and output parameters involved in the modeling process are listed in *Table 2*.

Table 2. Range of input and output parameters.

Range of Variation	Input Variables				Output
	M	S	P	V	B
Minimum	2.6	4.5	4.1	7.64	1.2
Maximum	8.6	15.2	13.8	20.75	3.2

3.2 | Applied Artificial Neural Networks

Three types of ANN models that have been utilized in this research include the following widely known architectures: Multilayer Perceptron (MLP), Neuro-Fuzzy (NF), and Radial Basis Function (RBF). The selection of these models is motivated by their ability to create complex nonlinear models, learn from past data, and predict the output with a great degree of accuracy.

Various structures and configurations for each type of network were generated and examined to establish which network would provide the best prediction of the net profit of residential buildings.

Different structures of MLP with various hidden layers and neurons have been established to find out the most efficient architecture. The NF models have been developed by considering different types of membership functions and fuzzy inference techniques for checking out their prediction skills. Besides, RBFs have also been considered to assess their modeling capacity with respect to financing strategies and profit-making projects.

Table 3 illustrates all models used along with the neural network structure adopted for this study.

Table 3. Architecture structure of ANN models.

Network	Input Variables	Output
MLP	V, P, S, M	B
NF	V, P, S, M	B
RBF	V, P, S, M	B

3.3 | Error Evaluation Indices

Several statistical indices have been used in this work to measure the effectiveness and predictive efficiency of ANNs. These measures quantify the level of correspondence between the observed and predicted results and have been extensively used in many studies involving neural network modeling. The measures chosen for use in this study are given below.

The correlation coefficient (R) is among the most common indicators that quantify the correlation between the predicted and observed data. The correlation coefficient value lies between -1 and +1, where values close to +1 show a higher correlation and better accuracy of predictions.

Correlation coefficient is computed as follows:

$$R = \frac{\sum(x-\bar{x})(y-\bar{y})}{\sqrt{\sum(x-\bar{x})^2 \sum(y-\bar{y})^2}}. \tag{1}$$

$$|R| \geq 0.8. \tag{2}$$

$$0.2 < |R| < 0.8. \tag{3}$$

$$|R| < 0.2. \tag{4}$$

In this study, the correlation coefficient (R) was used to evaluate the degree of correlation between the actual values and the predictions generated by the MLP neural network models.

3.4 | Neural Network Model Implementation

All of the ANNs were designed and constructed using the software MATLAB R2018a. To begin with, the MLP network, which is known as one of the most effective and extensively utilized types of neural networks, was first designed with the help of one hidden layer and two hidden layers. Various neuron counts for the hidden layers were used to come up with the optimal design.

Training was conducted for the MLP model using the dataset provided, and the performance of the various network configurations was assessed on the basis of the error criteria considered. An illustration of the performance of the MLP training is shown in *Fig. 2* below.

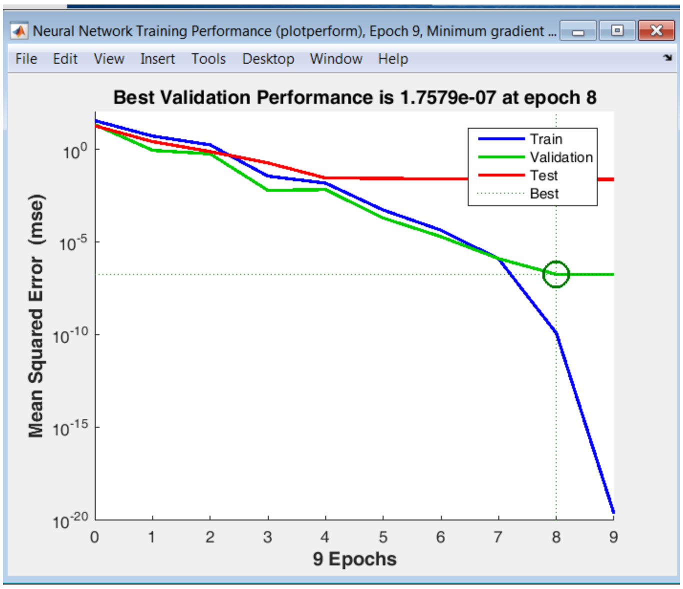


Fig. 2. An Example of MLP Training.

The critical issue that arises when modeling the MLP network is the number of layers and the number of neurons present in each layer, which can be established through trial and error. The following table shows error indices with respect to various structures of the MLP network having one hidden layer.

Table 4. Error indices for the MLP network with one hidden layer (MLP1).

Evaluation Data				
Hidden Layer Neurons	**Correlation**	**RMSE**	**Max Error**	**Sum of Squared Errors**
4	0.80	0.144	0.900	5.400
8	0.96	0.120	0.504	3.240
12	0.88	0.132	0.708	3.960
16	0.88	0.0996	0.420	1.800
20	0.98	0.0804	0.240	1.188
24	0.93	0.0864	0.372	1.320
30	0.98	0.1056	0.360	1.920
Training Data				
Hidden Layer Neurons	**Correlation**	**RMSE**	**Max Error**	**Sum of Squared Errors**
12	0.88	0.0960	0.540	8.160
16	0.94	0.0672	0.456	3.720
20	0.98	0.0660	0.432	3.720
30	0.95	0.0672	0.420	3.840
Testing Data				
Hidden Layer Neurons	**Correlation**	**RMSE**	**Max Error**	**Sum of Squared Errors**
12	0.96	0.1020	0.528	2.160
16	0.98	0.0948	0.264	1.560
20	0.97	0.0960	0.360	1.620
30	0.95	0.0972	0.324	1.680

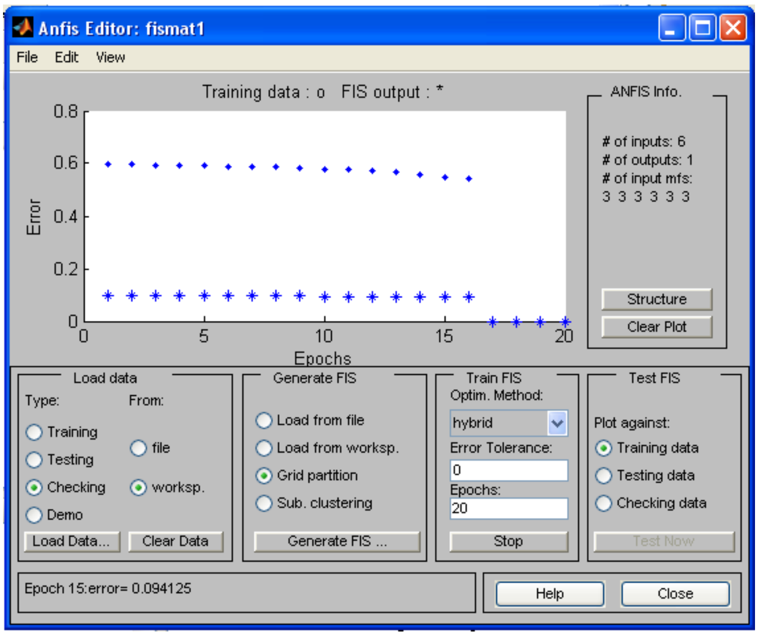
In *Table 5*, the values of the error indices are shown depending upon the architectures of the MLP neural network having two hidden layers. In choosing the right architecture for the MLP neural network, it is necessary to note that it is imperative to minimize the error index and maximize the correlation coefficient value.

Table 5. Error indices for the MLP network with two hidden layers (MLP2).

Evaluation Data					
Hidden Layer 1	**Hidden Layer 2**	**Correlation**	**RMSE**	**Max Error**	**Sum of Squared Errors**
4	4	0.73	0.1296	0.8100	4.8600
8	8	0.86	0.1080	0.4536	2.9160
12	12	0.79	0.1188	0.6372	3.5640
16	16	0.97	0.08964	0.3780	1.6200
20	20	0.97	0.07236	0.2160	1.0692
24	24	0.98	0.07776	0.3348	1.1880
30	30	0.96	0.09504	0.3240	1.7280
Training Data					
Hidden Layer 1	**Hidden Layer 2**	**Correlation**	**RMSE**	**Max Error**	**Sum of Squared Errors**
12	12	0.95	0.08640	0.4860	7.3440
16	16	0.96	0.06048	0.4104	3.3480
20	20	0.98	0.05940	0.3888	3.3480
30	30	0.92	0.08640	0.4860	7.3440
Testing Data					
Hidden Layer 1	**Hidden Layer 2**	**Correlation**	**RMSE**	**Max Error**	**Sum of Squared Errors**
12	12	0.93	0.09180	0.4752	1.9440
16	16	0.91	0.08532	0.2376	1.4040
20	20	0.97	0.08640	0.3240	1.4580
30	30	0.94	0.08748	0.2916	1.5120

4 | Fuzzy Neural Network Structure

A fuzzy neural network, similar to the MLP, operates according to artificial intelligence algorithms; however, the weight allocation mechanism depends on the categorization of input data. An example of how to train such a network is illustrated in *Fig. 3*.



ANFIS Info.
# of inputs: 6
# of outputs: 1
# of input mfs:
3 3 3 3 3 3

Load data
Type: ○ Training ○ Testing ● Checking ○ Demo
From: ○ file ● worksp.

Generate FIS
○ Load from file
○ Load from worksp.
● Grid partition
○ Sub. clustering

Train FIS
Optim. Method: hybrid
Error Tolerance: 0
Epochs: 20

Test FIS
Plot against: ● Training data ○ Testing data ○ Checking data

Epoch 15:error= 0.094125

Fig. 3. An example of NF network training.

The fuzzy neural network structure that gives the best performance can be determined through changes made to the membership functions, and based on *Table 6*, error indicators for various structures have been provided.

Table 6. Error indices for the NF neural network.

Training Data				
Number of Membership Functions	**Correlation**	**RMSE**	**Max Error**	**Sum of Squared Errors**
2	0.72	0.1296	0.8100	4.8600
3	0.86	0.1080	0.4536	2.9200
Testing Data				
Number of Membership Functions	**Correlation**	**RMSE**	**Max Error**	**Sum of Squared Errors**
2	0.79	0.0864	0.4860	7.3440
3	0.84	0.06048	0.4104	3.3480

5 | Radial Basis Function Neural Network Structure

In the previous chapter, it was noted that RBF networks use Gaussian kernels, and the main criterion that affects the structure of ANNs in such networks is the number of neurons used in the Gaussian kernels. Therefore, in this part, attempts have been made to find the optimal structure of this kind of neural network through changing the number of neurons used in the Gaussian kernel, as well as evaluating the efficiency of the neural network through observing the error indices.

Values of the error index of this type of neural network can be found in *Table 7*.

Table 7. Evaluation indices of RBF network structures with six input parameters.

Training Data				
Number of Gaussian Kernel Neurons	**Correlation**	**RMSE**	**Max Error**	**Sum of Squared Errors**
250	0.88	0.0374	0.363	1.320
500	0.89	0.0275	0.121	0.693
1000	0.86	0.0440	0.330	1.815
Testing Data				
Number of Gaussian Kernel Neurons	**Correlation**	**RMSE**	**Max Error**	**Sum of Squared Errors**
250	0.80	0.1012	0.495	3.190
500	0.79	0.1100	0.825	4.620
1000	0.77	0.1210	0.462	5.115

5.1 | Evaluation of Model Accuracy

Selection of optimal structures of neural networks of various types will eventually end up in the choice of the most appropriate structure through comparison among them all. For this purpose, from the results in *Table 8* and based on the comparison of performances of various neural networks, the MLP neural network that has two layers of 20 neurons emerges as the best-performing structure among the four other networks.

As a result, this network is chosen as the most effective one in predicting the optimal housing finance approach.

Table 8. Error indices for evaluating the optimal structure.

Evaluation Data					
Network	**Hidden Neurons**	**Correlation**	**RMSE**	**MAXAE**	**SSE**
MLP	20	0.97	0.07236	0.216	1.0692
Training Data					
Network	**Hidden Neurons**	**Correlation**	**RMSE**	**MAXAE**	**SSE**
MLP	20	0.98	0.0594	0.3888	3.348
NF	3	0.86	0.108	0.4536	2.92
RBF	250	0.88	0.0374	0.363	1.32
Testing Data					
Network	**Hidden Neurons**	**Correlation**	**RMSE**	**MAXAE**	**SSE**
MLP	20	0.97	0.0864	0.324	1.458
NF	3	0.84	0.06048	0.4104	3.348
RBF	—	0.80	0.1012	0.495	3.19

5.2 | Neural Network Model Sensitivity Analysis

Since ANNs work as a closed loop system, they do not give any concrete reasons about the relationship between input parameters and output. The sensitivity analysis technique is also called what-if or simulation analysis. In this method, an output for a decision is estimated by using a number of variables. With the help of setting up a number of variables, the impact of change in one of the variables on output can be assessed.

It is a technique that allows one to compute with precision the effect on the Net Present Value (NPV) of a project due to the change in one of the analyzed variables, assuming that the rest of variables do not change. To start with, a base case scenario has to be established by using input variables.

As widely acknowledged, there are several factors that determine the project's cash flows which are characterized by stochastic behavior. It means that an exact prediction of the cash flows cannot be made by any business entity. In addition, the change in a particular factor will result in changes in the net cash flows generated by a particular project. To address the issue, sensitivity analysis is utilized and examines the effect of changes in one factor on the NPV, assuming that all other factors are constant.

To do this, the base case should be determined based on the most probable input estimates. Following the estimation of such parameters as sales volume, selling price, fixed cost, and variable cost, several "what-if" situations arise. For instance, what if the sales drop by 20% from the forecasted number? Or, what if the variable cost ratio increases from 60% to 65%?

Sensitivity analysis gives responses to the queries listed above. In sensitivity analysis, one varies a variable within a certain percentage from the expected level in order to determine a new NPV. The use of NPV calculations enables the investor to analyze different scenarios and the risks involved.

It should be noted that the objective of using sensitivity analysis is to provide a realistic view of a project under consideration, taking into account the optimistic and pessimistic sides.

For instance, if there is an approximate rise of 20% in the fixed costs of manufacturing intercoms, what effect will it have on the break-even point?

$$\mathrm{BEP}_2 = \frac{508620}{11875000 - 7800000} = 124.815. \tag{5}$$

If the selling price subsequently decreases by 5%, then the break-even point will change as follows:

$$\mathrm{BEP}_2 = \frac{508620}{11875000 - 7800000} = 124.815. \tag{6}$$

In conclusion, as can be observed, changes in fixed costs and the weighted price of the product have a significant impact on the break-even point.

In addition to being involved in the prediction of variables by employing optimistic and pessimistic estimates, probability analysis also extends the horizon of analysis and identifies the possibility of events taking place for each value of a variable.

Probability analysis is performed in terms of preparing the project in order to make the estimation of prices and profitability more accurate. In addition to predicting variables through optimistic and pessimistic estimates, it also considerably extends the field of analysis and calculates the probability of events taking place for each value of a variable. Such an operation necessitates judgments from people who possess adequate experience in the subject matter under consideration. Through probability analysis, the number of calculations increases immensely due to the fact that for each variable, a lot of calculations take place.

5.2.1 | Optimal model evaluation

In this research work, the sensitivity analysis was carried out using four input parameters. In sensitivity analysis, 200 data points were chosen within the four-dimensional input parameter space in accordance with the normal distribution function. The values were generated using Simlab 3.0 software. Both the absolute and relative sensitivity of the output parameter with respect to the input parameters was considered while assessing their sensitivity level.

Table 9 shows the absolute sensitivity of the output parameter with respect to the input parameters.

Table 9. Relative derivatives of the output parameter with respect to inputs.

Input Parameter	Maximum	Minimum	Mean	Standard Deviation
V	3.6405	0.3971	1.0450	0.5885
S	2.8809	-1.3398	1.6302	1.0824
M	1.8612	-12.9580	-1.7523	1.3068
P	5.7798	-19.0740	-1.5697	1.5257

Moreover, in order to study the relationship between the variations of the output and input parameters, relative sensitivity analysis through relative derivatives was performed. The mean values of relative sensitivities with regard to input parameters are listed in *Table 10*.

Table 10. Relative sensitivity values of the output with respect to inputs.

Output	Input Variable	Relative Derivative
B	V	-0.8352
B	S	0.2706
B	P	-3.2120
B	M	-1.2815

As illustrated in *Table 10*, there are three input parameters having approximately equal values of sensitivity, implying that the three parameters affect the total profit equally. The single most significant parameter is parameter (P) when assessed using either absolute or relative sensitivity measures.

6 | Conclusion

Housing finance is regarded as one of the crucial components contributing to the success of a housing project, and the choice of the most suitable method of financing could affect directly the profit from the project, its execution period, and its risk level. Considering the complicated interrelations between different economic, financial, and operational parameters influencing the construction projects, the use of traditional decision-making techniques would be not enough for meeting the emerging requirements in this area. Thus, the implementation of advanced technologies and application of artificial intelligence in analysis and decision-making has been identified as a quite efficient solution.

In this research, the possibility of applying ANNs as a highly-efficient machine learning technique for choosing the optimal way of financing a construction project has been assessed. Reviewing relevant literature revealed that ANNs had been used in several fields related to construction management, namely, construction cost estimation, prediction of time consumption, identification of project risks, and analysis of project economic parameters. Moreover, the analysis of the obtained results demonstrated that neural network models proved their ability to reveal complicated nonlinear relations between variables influencing projects' performance.

According to theoretical concepts and empirical studies, it is predicted that the implementation of ANNs will help to analyze financial, economic, and operational aspects to choose the best possible financing strategy for residential constructions, thus enhancing the effectiveness of decision-making processes conducted by investors and constructors. Such models are not only expected to help decrease investment risks but also optimize financial resource management, improve economic efficiency, and increase the overall effectiveness of construction projects.

In general, the outcomes of this study can be used as a good basis for creating effective decision support systems in construction financial management. It is also necessary to recommend further researchers to apply deep learning algorithms with larger sets of data from housing project financing to create better predictive models.

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