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Analysis and Optimization of Housing Construction Financing Methods Using Artificial Neural Networks

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Abstract

Financing housing construction projects has always been considered one of the most significant challenges in the construction industry. Selecting an appropriate financing method has a direct impact on project profitability, execution time, and overall project success. The complexity of the relationships among economic, technical, and managerial factors has reduced the efficiency and accuracy of traditional decision-making approaches in many cases. Therefore, this study employs Artificial Neural Networks (ANNs), as one of the modern Artificial Intelligence (AI) tools, to optimize the selection of financing methods in housing construction projects. In this research, three types of neural networks, including the Multi-Layer Perceptron (MLP), Neuro-Fuzzy Network, and Radial Basis Function (RBF) Network, were designed and modeled. Influential parameters related to financing and construction costs were selected as input variables, while the final project profit was considered the output variable of the models. To determine the optimal structure, various models with different architectures and functions were trained and evaluated using error indices. Furthermore, sensitivity analysis was conducted on the selected models to assess the impact of each input variable on model performance. The results revealed that the MLP network outperformed the other models in terms of prediction accuracy and optimization capability for housing financing methods. In addition, the sensitivity analysis indicated that the pre-sale parameter had the greatest influence on the final profit and financial success of construction projects. The findings of this study demonstrate that ANN can serve as an intelligent and efficient tool for improving financial decision-making processes in housing construction projects and reducing project-related economic risks.

Keywords: Housing finance, Artificial neural network, Optimization, Multi-layer perceptron, Sensitivity analysis, Construction management.

1 | Introduction

Today, the construction industry is recognized as one of the most important economic and infrastructural sectors in countries, playing a decisive role in economic development, job creation, and investment growth. Among construction activities, housing projects require substantial capital investment and are highly influenced by economic conditions and implementation complexities. Consequently, these projects demand

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accurate planning and efficient financial resource management. Selecting an appropriate financing method is considered one of the key success factors in construction projects, as any improper financial decision may lead to increased costs, reduced profitability, project delays, and even project failure.

With the expansion of financial markets and the diversification of capital procurement methods in the construction sector, selecting the optimal financing strategy has become a complex multi-criteria decision-making problem. Factors such as construction costs, inflation rates, housing market conditions, pre-sale levels, bank loan interest rates, payback periods, and investment risks all significantly influence the financial success of projects. Moreover, the relationships among these variables are often nonlinear and uncertain, making traditional analytical methods insufficient for addressing such complexities.

In recent years, advances in Artificial Intelligence (AI) and machine learning technologies have provided effective tools for solving complex engineering and managerial problems. Artificial Neural Networks (ANN), as one of the most important AI techniques, possess a high capability for pattern recognition, nonlinear modeling, and prediction of complex system behavior. Inspired by the structure of the human brain, these networks can extract hidden patterns from historical data and predict future system behavior. Consequently, the application of ANNs in civil engineering, construction management, cost estimation, and financial optimization has attracted considerable attention among researchers in recent years.

The present study aims to investigate and optimize financing methods in housing construction projects using different ANN models, including the Multi-Layer Perceptron (MLP), Neuro-Fuzzy Network, and Radial Basis Function (RBF) Network. By utilizing real project data and analyzing the behavior of financing-related variables, this research seeks to develop an intelligent model for predicting final project profit and identifying the most suitable financing method. In addition, sensitivity analysis is employed to evaluate the influence of each input parameter on the financial performance of the project.

The significance of this research lies in its potential contribution to civil engineers, project managers, investors, and decision-makers in the construction sector by enabling them to select the most appropriate financing strategy based on scientific and data-driven approaches, thereby reducing economic risks. Furthermore, the implementation of intelligent methods in the financial management of construction projects can enhance capital productivity, improve decision-making processes, and strengthen the economic performance of the housing industry.

2 | Literature Review

In recent years, the application of intelligent methods, particularly ANN, in construction management, cost estimation, and financial optimization of construction projects has grown significantly. The complexity of relationships among economic, financial, and operational variables in construction projects has encouraged researchers to adopt machine learning and AI techniques to improve prediction accuracy and decision-making processes.

Early studies on the application of ANNs in civil engineering demonstrated the strong capability of these methods in modeling nonlinear relationships and analyzing complex datasets. Initial research mainly focused on construction cost estimation, project duration prediction, and risk analysis. Gradually, the use of neural networks in financial management and the optimization of financing methods for construction projects also gained increasing attention.

Williams [1] applied the backpropagation algorithm to predict fluctuations in construction cost indices and demonstrated that neural networks provide greater accuracy than traditional methods in cost trend analysis. Similarly, Hegazy and Ayed [2] utilized neural networks for highway project cost estimation, and their findings showed that ANN models could significantly reduce cost prediction errors.

Chua et al. [3] developed a neural network-based model to identify the key factors affecting budget performance in construction projects. Their results indicated that ANNs have a strong capability to analyze incomplete data and complex relationships among project financial variables. In another study, Alqahtani and

Whyte [4] applied neural network techniques to life-cycle cost analysis in construction projects and achieved satisfactory prediction accuracy.

In recent years, research attention has increasingly shifted toward hybrid intelligent models and advanced optimization algorithms. In 2025, Abumahfouz et al. [5] proposed a hybrid model combining the Fuzzy Analytic Hierarchy Process (FAHP) with ANN for estimating construction project costs. Their findings demonstrated that integrating multi-criteria decision-making methods with ANNs improves prediction accuracy and reduces uncertainty in financial decision-making.

Hassoun et al. [6], in another 2025 study, investigated the application of ANN and the XGBoost algorithm in predicting productivity in residential construction projects. The results showed that AI-based models can accurately predict both financial and operational project performance.

In the same year, Gao and Zhao [7] proposed a neural network model optimized using a genetic algorithm for estimating investment costs in prefabricated buildings. Their study revealed that integrating evolutionary algorithms with ANNs improves decision-making accuracy and reduces cost estimation errors.

Kim [8] also employed AI-based models in 2025 to predict costs and environmental impacts of highway projects. The findings demonstrated that neural networks are capable of identifying complex cost patterns and assisting project managers in financial planning.

In one of the most recent studies, an intelligent model integrating the FAHP and the GA-BP neural network was developed for predicting residential construction costs [9]. The model was trained using real construction data, and the results indicated that intelligent algorithms can serve as effective tools for financial planning and capital management in construction projects.

Furthermore, the study by Rosenbaum and Bartels [10] in 2026 showed that the use of AI technologies in construction management not only improves decision-making accuracy but also enhances risk management and project cost control processes.

In another study, the BuildCES researchers [11], [12] proposed a framework based on Building Information Modeling (BIM), blockchain, and AI for predictive management of construction projects. Within this framework, deep learning models were employed for material cost prediction, risk control, and project financial optimization.

A review of previous studies indicates that although numerous investigations have focused on cost estimation, financial performance prediction, and construction project optimization using ANN, limited research has directly addressed the optimization of financing methods in housing construction projects. Therefore, the present study attempts to develop an intelligent framework for selecting the optimal financing method in housing construction projects through the application of various ANN models and sensitivity analysis of influential parameters.

3 | Research Methodology

In this study, the results obtained from 100 housing projects constructed using different financing methods were utilized. These projects were implemented in the provinces of Tehran, Alborz, and other regions, and their structural and financial parameters are presented in *Table 1*.

Considering the factors influencing project financing, the financing method parameters, including bank loans (V), pre-sale (P), personal initial capital (S), and joint venture participation in construction (M), were considered as the input variables. The final net profit (B) was selected as the output parameter of the model. A sample of the input data used for training the ANN is presented in *Table 1*.

Table 1. Sample of the input database (values in Billion Tomans).

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

3.1 | Neural Network Architecture

3.1.1 | Input Variables

Considering the factors influencing financing strategies, the financing method parameters, including bank loans (V), pre-sale (P), personal initial capital (S), and joint venture participation in construction (M), were selected as the input variables, while the final net profit (B) was considered the output parameter of the model. It should be noted that the selection of input variables was also based on their significant influence on the final project profit.

At this stage, neural network models with four input parameters were employed. The input parameters were derived from the structural and financial characteristics of the construction projects.

The output parameter was defined as the final net profit obtained from the project, which was considered the sole output variable in the modeling process. The ranges of variation for the input and output parameters are presented in *Table 2*.

Table 2. Range of input and output parameters.

Range of Variations	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 | Implementation of the Neural Network Model

The neural network models were developed and implemented using MATLAB (2018a) software. Initially, the MLP, as one of the most successful ANN architectures, was modeled with one and two hidden layers. A sample of the training curve of this network is presented in *Fig. 1*.

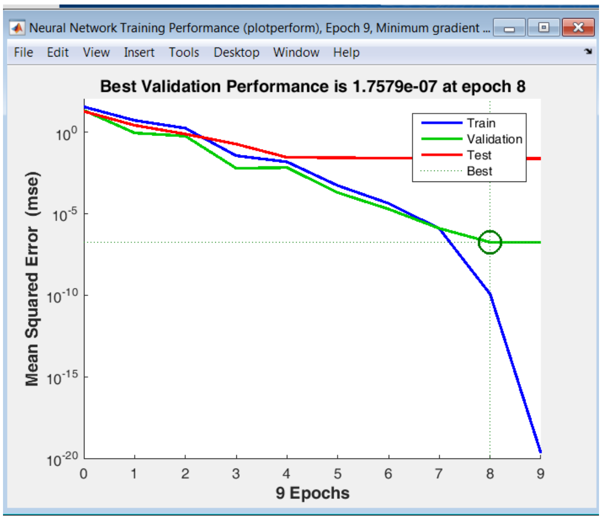

Fig. 1. Sample training curve of the MLP network.

The most important factor in modeling the MLP network is the number of hidden layers and the number of neurons in these layers, which are determined through a trial-and-error process. *Table 3* presents the values of the error indices based on different structures of the MLP network with a single hidden layer.

Table 3. Error indices for the MLP1 network.

Hidden Layer Neurons	Correlation	RMSE	Maximum Error	Sum of Squared Errors
4	0.80	0.1440	0.900	5.400
8	0.96	0.1200	0.504	3.240
12	0.88	0.1320	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
Hidden Layer Neurons	**Correlation**	**RMSE**	**Maximum Error**	**Sum of Squared Errors**
4	0.80	0.1440	0.900	5.400
8	0.96	0.1200	0.504	3.240
12	0.88	0.1320	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
Hidden Layer Neurons	**Correlation**	**RMSE**	**Maximum 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

Table 4 presents the values of the error indices based on different architectures of the MLP network with two hidden layers. The most important criterion in selecting an appropriate MLP neural network architecture is that the error indices should be minimized, while the correlation coefficient should be maximized.

Table 4. Error indices for the MLP2 network.

Hidden Layer 1 Neurons	Hidden Layer 2 Neurons	Correlation	RMSE	Maximum 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
Hidden Layer 1 Neurons	**Hidden Layer 2 Neurons**	**Correlation**	**RMSE**	**Maximum Error**	**Sum of Squared Errors**
12	12	0.95	0.0864	0.4860	7.3440
16	16	0.96	0.06048	0.4104	3.3480
20	20	0.98	0.0594	0.3888	3.3480
30	30	0.92	0.0864	0.4860	7.3440
Hidden Layer 1 Neurons	**Hidden Layer 2 Neurons**	**Correlation**	**RMSE**	**Maximum Error**	**Sum of Squared Errors**
12	12	0.93	0.0918	0.4752	1.9440
16	16	0.91	0.08532	0.2376	1.4040
20	20	0.97	0.0864	0.3240	1.4580
30	30	0.94	0.08748	0.2916	1.5120

3.2.1 | Neural Fuzzy Network Structure

The neural-fuzzy network, similar to the MLP, is also based on AI principles; however, its weight assignment process is based on the classification of input data. A sample of the training process of this network is presented in *Fig. 2*.

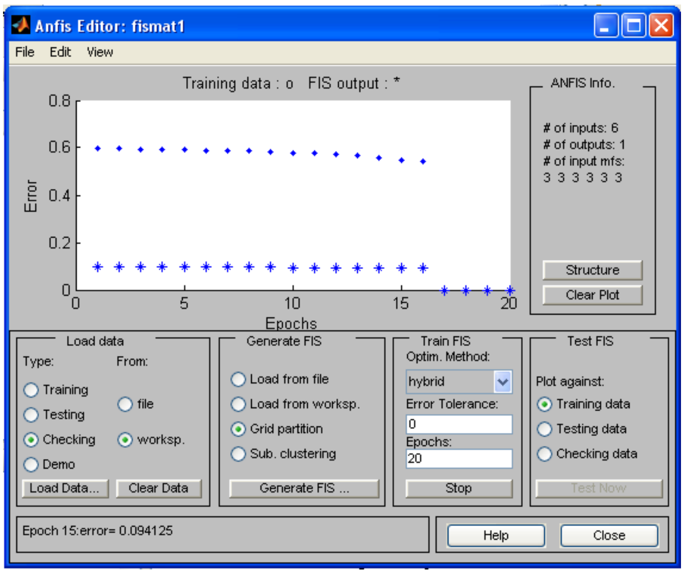

Fig. 2. Sample training process of the neural-fuzzy network.

To determine the optimal structure of the neural-fuzzy network, variations in its membership functions were employed. Accordingly, the error indices for different network structures are presented in *Table 5*.

Table 5. Error indices for the neural-fuzzy network.

Number of Membership Functions	Correlation	RMSE	Maximum Error	Sum of Squared Errors
2	0.72	0.1296	0.810	4.860
3	0.86	0.1080	0.4536	2.920
Number of Membership Functions	**Correlation**	**RMSE**	**Maximum Error**	**Sum of Squared Errors**
2	0.79	0.0864	0.4860	7.344
3	0.84	0.06048	0.4104	3.348

3.2.2 | Radial Basis Function Network Structure

As previously mentioned, RBF networks operate based on Gaussian kernels. The most important factor in determining the optimal structure of these networks is the number of neurons in the Gaussian kernels. In this section, different numbers of Gaussian neurons are used to determine the optimal structure of the RBF network, and its performance is evaluated by examining error indices.

The error indices for different RBF network structures are presented in *Table 6*.

Table 6. Performance indices of the RBF network with six input parameters.

Number of Gaussian Neurons	Correlation	RMSE	Maximum Error	Sum of Squared Errors
250	0.88	0.0374	0.363	1.32
500	0.89	0.0275	0.121	0.693
1000	0.86	0.0440	0.330	1.815
Number of Gaussian Neurons	**Correlation**	**RMSE**	**Maximum Error**	**Sum of Squared Errors**
250	0.80	0.1012	0.495	3.19
500	0.79	0.1100	0.825	4.62
1000	0.77	0.1210	0.462	5.115

3.3 | Model Accuracy Evaluation

The identification of optimal structures for each type of ANN must ultimately lead to the selection of the best-performing model through comparative analysis. In this section, based on a comparison of different neural network models, the MLP with two hidden layers containing 20 neurons demonstrates the best performance compared to the other three models. Therefore, this model is selected as the most effective approach for predicting the optimal housing financing method.

Table 7. Error indices for optimal model evaluation.

Network Type	Neurons	Correlation	RMSE	MAXAE	SSE
MLP	20	0.97	0.07236	0.216	1.0692
Network Type	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
Network Type	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	250	0.80	0.1012	0.495	3.19

3.4 | Sensitivity Analysis of the Neural Network Model

Since ANNs operate as closed box systems, they do not explicitly explain the influence of input parameters on the output. Sensitivity analysis, also known as "what-if" or simulation analysis, is used to address this limitation. This method predicts the output of a decision model under a range of input variables, allowing analysts to determine how changes in a variable affect the output.

Sensitivity analysis begins with a base-case scenario constructed using the expected values of input variables. Since many variables influencing project cash flow follow probabilistic distributions, precise prediction of cash flows is not possible. Changes in key variables, such as the number of units sold, directly affect net cash flow.

In this study, sensitivity analysis was performed on four input variables. A total of 200 data points in a four-dimensional input space were generated assuming a normal distribution using SimLab 3.0 software. Sensitivity was evaluated using both absolute and relative derivatives of the output variable with respect to the input variables. *Table 8* presents the absolute sensitivity indices.

Table 8. Absolute sensitivity of output with respect to input variables.

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	-12.958	-1.7523	1.3068
P	5.7798	-19.074	-1.5697	1.5257

For further investigation, relative sensitivity values were also calculated using normalized derivatives. The mean relative sensitivities are presented in *Table 9*.

Table 9. Mean relative sensitivity of output with respect to inputs.

Output	B
Input	V
Relative Derivative	-0.8352

As shown in *Table 9*, three input parameters exhibit relatively similar sensitivity values, indicating that these variables have approximately equal influence on the final profit. However, the most influential parameter in both absolute and relative sensitivity analysis is the pre-sale parameter (P).

4 | Conclusion

In this study, data from 100 housing projects constructed using different financing methods were utilized. These projects were carried out in Tehran, Alborz, and other regions, with structural and financial parameters as presented in *Table 1*.

Considering the influencing factors of financing, the parameters of financing methods, including bank loans (V), pre-sale (P), personal capital (S), and construction participation (M), were considered as inputs, while net profit (B) was defined as the output variable. A sample of the dataset is presented in *Table 1*.

Based on the selected input variables, three ANN models (MLP, NF, and RBF) were developed. Detailed model specifications are provided in *Table 3*. All models were implemented using MATLAB (2018a). Initially, the MLP, as one of the most successful neural networks, was modeled with one and two hidden layers, and its training curve is shown in *Fig. 1*.

The most critical factor in MLP modeling is the number of hidden layers and neurons, which is determined through trial and error. The optimal structure is selected based on minimizing error indices and maximizing the correlation coefficient.

The neural-fuzzy network also utilizes AI logic; however, its weight assignment is based on input data clustering. The training process is shown in *Fig. 2*.

RBF networks operate based on Gaussian kernels, and the key factor in their design is the number of Gaussian neurons. Different configurations were tested to determine the optimal structure.

Ultimately, comparative evaluation of all models showed that the MLP network with two hidden layers and 20 neurons achieved the best performance among all models. Therefore, it was selected as the most accurate model for predicting optimal housing financing strategies.

Since ANN models are black-box systems, sensitivity analysis was applied to interpret input-output relationships. A total of 200 samples were generated using SimLab 3.0 under normal distribution assumptions. Both absolute and relative sensitivity analyses were performed.

Results indicated that although three input variables had similar influence on project profit, the pre-sale parameter (P) was the most influential factor in both absolute and relative sensitivity measures.

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