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Research Article

Profitability Prediction for Construction Projects by Neural Network with Autoregressive Model: A Detail Analysis

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Abstract - *This study examines the variables influencing the calculation of the profit ratio throughout the building project from the tendering process to completion. To identify the key elements controlling the calculation of profit ratio, the impact of projects on aspects by owner, engineer, contractor, clients, manufacturer and labourers was examined. Delay fines and client experience were the least significant in determining the profit ratio. The net profit was decided by the primary determinants of a company. Two distinct net profit models were created: the Autoregressive Integrated Moving Average Model (ARIMA) and the Artificial Neural Networks (ANN)-based dispute attribute prediction model. The objective of this optimisation issue is to minimise the aforementioned error between the target and output by determining the weights and biases of the ANN. The ANN methodology was used to ensure that these elements are the main factors influencing project disputes and to create a dispute prediction model for them. In this regression analysis, the factors influencing the profitability of construction are analysed clearly for better understanding. With inputs that reflect factors that were ranked as the most influential, an ANN was created to forecast the project performance model. The proposed models reduce the degree of construction risk in the profit ratio and enable project managers to concentrate on the critical success criteria.*

Keywords *- Construction management, Profitability, Artificial Neural Networks, ARIMA.*

1. Introduction

The construction sector makes a substantial contribution to the nation's economic development. An industry that is predicted to grow is construction, which makes a significant contribution to the total GDP. Due to the complications of the construction business, delays in projects have become a common problem [1]. Businesses must make an effort to execute their projects with excellent performance to satisfy client demands by adhering to the established financial, schedule, and quality constraints [2]. It is challenging to collect input data for the cost estimation process because the scope of the task is rarely specified, which could lead to imprecise and erroneous calculations. Because more project requirements are established, there is a greater likelihood of producing estimates that are more accurate, the more the project scope is known [3]. Because of their demonstrated Digital technologies, such as in the construction sector, to grow sustainably, control, estimate, optimise, forecast, and decision-making accuracy and efficiency can be increased through the application of Artificial Intelligence (AI) and machine learning [4].

In residential building construction, techniques such as neural network analysis, time-series analysis, regression analysis, and grey theory are commonly used in numerous studies. [5, 6]. The project will face greater risks, have fewer resources available, and require more overtime to finish if the bidding price is lower. To make up for the loss in profit, contractors may reduce the scope of their work or lower the quality of their construction projects when profits are low [7]. On the other hand, the degree of complexity, work availability, competitiveness, investment risks, and contract size were the primary determinants of bid markup for major contractors [8]. Larger contractors gave more weight to the building task's difficulty when determining a bid markup than did medium-sized companies [9, 10]. The success or failure of the prediction models depends on how reliable the prediction approach is [11]. It will take more computation and produce less accurate forecasting results if variables that have minimal bearing on project costs are used to predict costs [12]. The involvement of consultants, specialists, contractors, subcontractors, owners, and designers, among others. Describe the construction projects' multidisciplinary perspective. As the project's scope expands, the number of participants must likewise grow, which always results in conflict [13]. Gaining an understanding of the real mechanisms and relationships regulating the process may be challenging due to this lack of physical interpretability [14, 15]. In the regression analysis of ANN, the parameters of the results are more accurate compared to other analysis platforms of quantitative research. In this analysis, Mean Square Error, Mean Absolute Error, Mean Absolute Percentage Error, and Coefficient of Determination clearly analyse the factors influencing the profitability of the construction budget as expected in every project.

2. Literature Review

According to Cheng, M. Y., *et al.*, in 2025, better project planning and resource allocation depend on accurate building cost and schedule estimation. These methods, however, fall short of capturing the complex patterns found in both time-dependent and time-independent data. For building costs and completion timeframes, the suggested model received values of 0.932 and 0.977 for the Reference Index (RI), respectively. These findings demonstrate the OMA-NN model's ability to generate exceptionally accurate projections, enabling stakeholders to make educated decisions that enhance project efficacy and success overall [16].

In 2019, from the beginning of a project to its completion, the construction sector produced a variety of data. There is a large amount of data and forms that are outside the scope of the industry's current project intelligence solutions for data management, integration, and analysis. Current methods for estimating profits are based on industry-wide or company-specific benchmarks. Since these standards do not fully fill the project-specific variances, they are frequently incorrect. Because of this, projects are inaccurately projected using uniform rates, which ultimately results in completely atypical margins from either underspending or overspending [17].

The efficient use of construction cost prediction may significantly ease construction cost control and management, as claimed by Ye, D. et al. in 2019 [18]. Consequently, this study suggests a unique construction project cost prediction system based on a particle swarm optimisation-guided BP neural network and enhances the BP neural network by utilising particle swarm optimisation techniques. This study leverages the benefits of particle swarm optimisation in the field of parameter optimisation to optimise BP neural networks with PSO methods, thereby addressing the limitations of BP neural networks updating weights and thresholds using the gradient descent methodology.

In 2024, El-Hazek et al. examined 267 responses to a questionnaire that was created to assess the significance of 35 factors influencing the profit ratio decision [19]. Consequently, this study suggests a unique construction project cost prediction system based on a particle swarm optimisation guided BP neural network by utilising particle swarm optimisation techniques. This study leverages the benefits of particle swarm optimisation in the field of parameter optimisation to optimise BP neural networks with PSO methods, thereby addressing the limitations of BP neural networks updating weights and thresholds using the gradient descent methodology. In 2024, El-Hazek et al. examined 267 responses to a questionnaire that was created to assess the significance of 35 factors influencing the profit ratio decision [19].

According to the findings, the majority of businesses in Egypt did not use any formulas or analysis to calculate the profit ratio for building projects. The most crucial elements for determining the profit ratio, according to the Relative Importance Index, were cash flow, economic stability, contract size, contract type, and degree of difficulty. The client's experience, safety regulations, and delay fines were the least significant factors in determining the profit ratio. The 35 factors affecting the profit ratio were whittled down to 12 important factors using Pareto analysis.

In 2023, Maya, R. et al. identified 34 parameters that influence the project's performance based on practitioner perspectives [20]. Seven inputs, representing six factors that were ranked as the most influential, were used in the building of the Artificial Neural Network (ANN) to predict the project performance model. Artificial Neural Network (ANN) applications in energy management, material testing and control, sustainable construction materials, infrastructure analysis and design, sustainable construction management, infrastructure functional performance, and sustainable maintenance management were examined for their environmental effects by Ahmed, M. et al. in 2022 [21]. The financial part focuses on financial management and construction productivity through the use of ANN applications. The social component looks at society, human values, and safety and health issues in the construction industry. The study shows how ANN approaches can be applied in a range of transdisciplinary settings to enhance the construction industry's long-term growth.

In order to estimate the FCC at an early project stage based on Contract Cost (CC), contract term, and project sector, Al-Gahtani et al. established an Artificial Neural Network (ANN) model in 2024 [22]. There are 135 construction projects in Saudi Arabia, which provided the data that was gathered and utilised for the ANN model. To get over the limited data, the Pasini method and the Zawadzkas and Turskis logarithmic algorithms were employed. The ANN model was then created in two phases. To improve the data in the first stage, anomalous data were identified using Absolute Percentage Errors (APE). In the second stage, the ANN was developed using the improved data. Lack of safety performance is a major challenge in many countries. In this study, the reasons for the high rate of accidents and fatalities in the construction sector were analysed, and the previous accidents were analysed to prevent injury. LLMs are a part of the deep learning model used to analyse the accident ratio on construction sites [23].

The ANN analysis is about two types of recycled construction waste that are in the reading of the input layer, and the result is obtained by regression analysis to get the parameter that was the ultimate bearing capacity on the output layer. The results help to find the best recyclable material in construction [24]. In the deep foundation pit construction sector, the LSTM-RN-ANN analysis has been used in this study to monitor from the edge of the pit. For this LSTM analysis. Root-mean-square error, average absolute error, and determination coefficient are used [25].

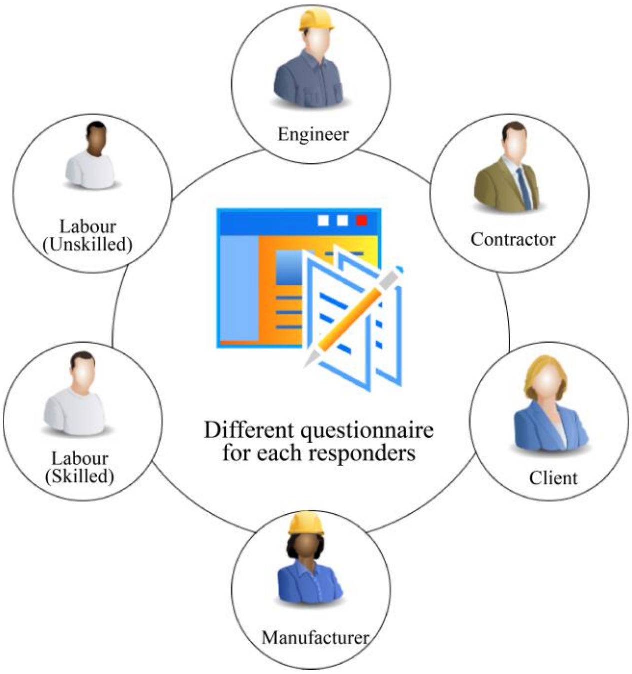

Fig. 1 Types of Respondents

3. Methodology of Profitability Analysis

To create a model for calculating the profit ratio for construction projects and to investigate the important aspects influencing the calculation of profit in these projects. To find out the significance of 35 elements influencing the profit ratio decision, a questionnaire was created, and 100 replies were examined. The objective of this study is to develop a mathematical framework for estimating any construction company's anticipated net profit. First, the primary factors of a company's net profit were determined. Two distinct net profit models were created, including the ARMIA model and the dispute attribute prediction model based on Artificial Neural Networks (ANN). The ANN methodology was used to ensure that these elements are the main factors influencing project disputes and to create a dispute prediction model for them.

The models reduce the degree of construction risk in the profit ratio and enable project managers to concentrate on the critical success criteria. The model can be used as a foundation for future improvements to the decision support system for construction management. With inputs that reflect factors that were ranked as the most influential, an ANN was created to forecast the project performance model. The characteristics of the project, the Client, Engineer, Manufacturer, Contractor, and the Skilled and Unskilled labour components were the survey categories in the region of Thanjavur, Thiruvarur, Nagapattinam, Mayiladuthurai, and Karaikal areas.

A questionnaire was created and given to the respondents, and twelve of the 35 factors that affected the profit ratio were deemed important. To determine the profit ratio for the various construction projects of the important components. Figure 2 illustrates the research stages in which this investigation is carried out.

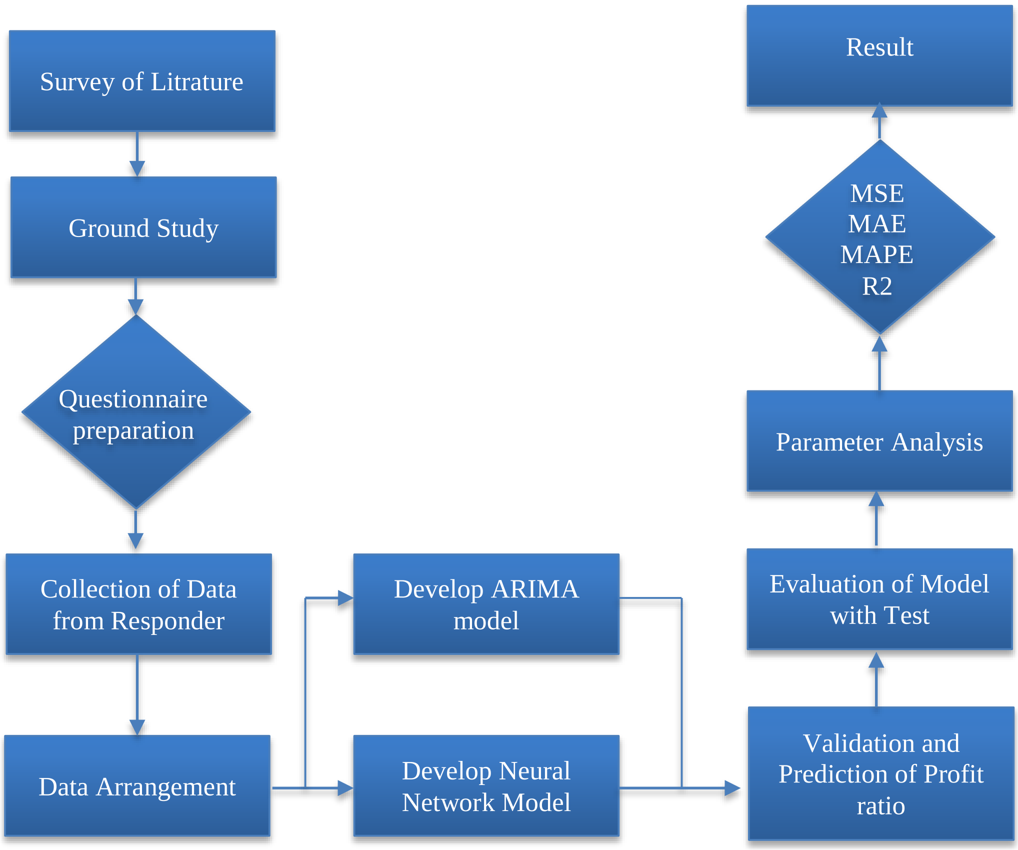

Fig. 2 Block diagram for research methodology

3.1. Questionnaire Preparation for Analysis

A questionnaire survey approach was employed to find out the influence of several elements on the project's cost. The design concept of the questionnaire is based on the literature survey.

Personal interviews and a questionnaire served as the foundation for the study. The significance of the delay factors was investigated using regression modelling and factor analysis. This emphasises how crucial it is to have more competent and experienced construction managers in addition to skilled workers to facilitate the industry's faster growth on a national and worldwide scale.

3.2. Profitability Prediction Model

ANN is a widely used method for modelling correlations between inputs and outputs, utilising units that behave similarly to neurons, and forecasting future values based on historical data. The input, hidden, and output layers are its three components. Weights are given to variables according to how they affect the final product. The ANN methodology was used to ensure that these elements are the main factors influencing project disputes and to create a dispute prediction model for them. ANN has been used to take into account the variables that affect the various project performance characteristics in Indian projects. The model will select the number of neurons and training parameters based on the dataset; thus, keep in mind that this technique may be applied to any dataset for worldwide analysis of construction.

3.3. Layers in Neural Network

A neural network's mathematical model contains an input layer, many hidden layers, and an output layer that corresponds to the transmitter, communicator, and receiver neurons, respectively. Figure 2 shows the layers of the ANN structure. The structure of a neural network depends on the number of layers, how many neurons are in each layer, and how each neuron is excited [26].

A variety of hidden-layer neurons $hl_1, hl_2 \ldots hl_3$ are recorded by the mystery layer, which then uses neurons to link them to the output layer. This layer $\delta_j$stores loads of the mystery layerγ_{ij} , as well as the weight of the data layer. Criterion (1) is used to evaluate the FFBN structure's main and inception functions.

$$F_b = \sum_{j=1}^{N} input_{i=1,2..n} \times \gamma_{ij} \tag{1}$$

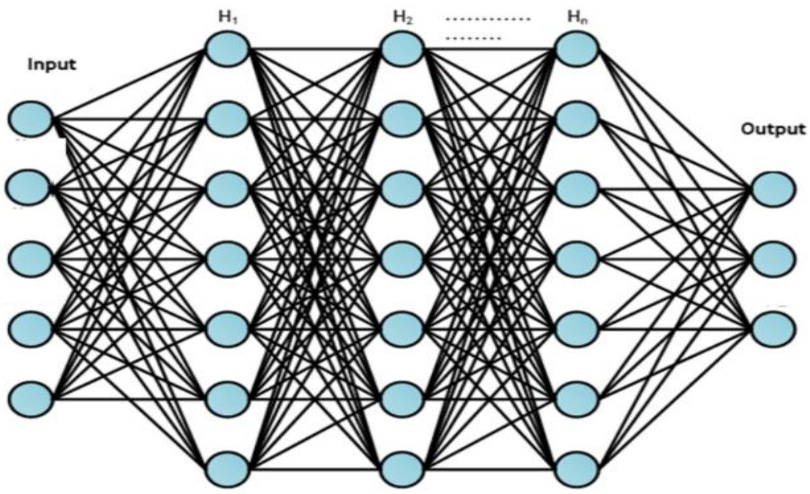

Fig. 3 Structure of neural network

3.4. Steps of Feed Forward Neural Networking

The primary objective, the role of sanctions, and the amount of data to be collected (N) are highlighted in Equation (1). Condition 1 selects the incitation function for the showcase's MSE evaluation.

After determining the health value of each option, cycle through the values of the best course of action. In this case, a low MSE rate denotes healthy health. In this instance, excellent health is indicated by a low MSE rate.

$$MSE = min\left(\frac{\sum_{i=1}^{D_N}(tv_i - Pv_i)^2}{Totaldata}\right) \tag{2}$$

By resurrecting the loads in a sanctioning function, the real value, which includes the expected value, the preliminary result Pv_i, the quantity of data and the base error rate, is discussed in Equation (2).

3.4.1. Training and Testing Model

By controlling network weights and biases, neural network training aims to reduce output inaccuracy. For ANNs, numerous learning algorithms have been created. In backpropagation, a network is continuously trained using input and the associated output to approximate a function and correlate the input with a particular output. The errors are propagated backwards once the inputs are delivered forward. Typically, training begins with random weights and biases, which the algorithm modifies to reduce errors [27]. And for testing the model, the purpose of operating validation was to test the performance of this trained network in analysing unknown data sets. The network will be operational if the results are good. If not, the proposed model suggests that the network needs to be modified or that more or better data is needed. The ability of the ANN model to predict a new output is then evaluated using 30% of the collected data.

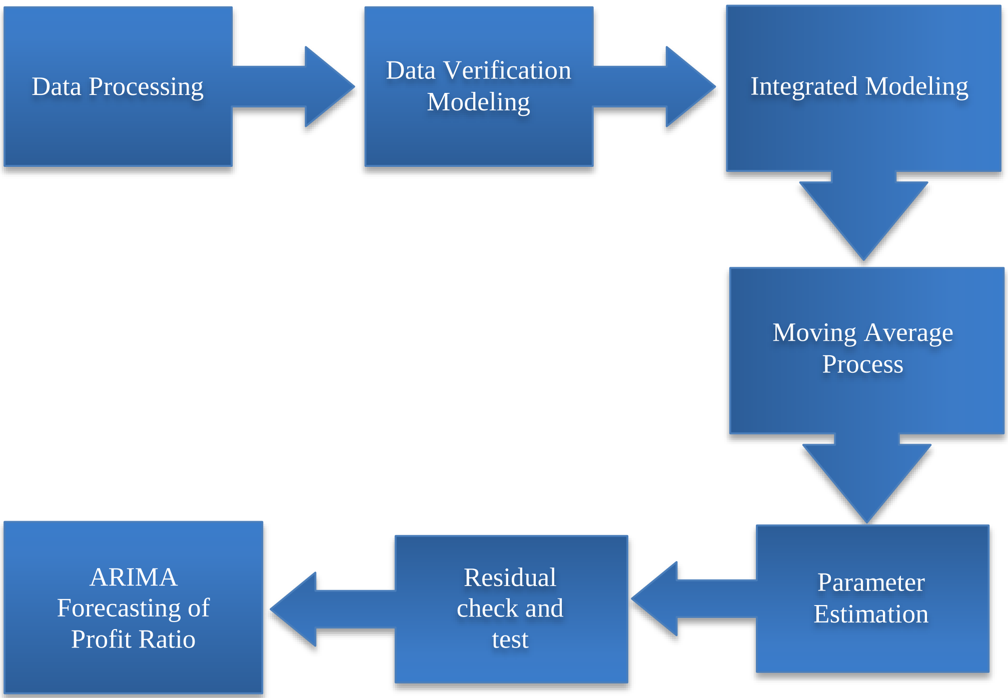

Fig. 4 Process of ARIMA modelling

3.5. Data Analysis by Autoregressive Integrated Moving Average Model

Time series can be represented using standard statistical models such as moving averages, exponential smoothing, and ARIMA, as shown in Figure 4.

Differentiating the data series is required in order to apply the ARMA model to non-stationary series. For example, an ARIMA model (x, y, z), where x is the number of moving averages, y is the number of differences, and z is the number of autoregressive terms.

3.5.1. Autoregressive Process

In a multiple regression model, we forecast the variable of interest using a linear combination of predictors. An autoregression model, which is a linear combination of the variable's historical values, is used to forecast the variable of interest.

Autoregression is a regression of the variable against itself, as the name suggests Q_t. It is provided by Equation (3) and is believed to be a linear function of the values that come before it in autoregressive models.

$$Q_t 1/4 \alpha_1 Q_{t1} \varepsilon_t \tag{3}$$

In literal terms, every observation is made up of a random component (random shock, ε) and a linear mixture of the previous observations. α1 is the self-regression coefficient of this equation.

3.5.2. Integrated Process

The behaviour of the time series may be affected by the cumulative influence of certain processes. Variations between observations for a process that is monitored at multiple time intervals may be relatively small or even oscillate around a fixed number, even if the behaviour of a series is unpredictable. The difference between two subsequent values is believed to be constant in an order 1 differentiation. Integral processes are defined via equations.

$$Q_t 1/4 \alpha_1 Q_{t1} \alpha_{t1} \tag{4}$$

Here, the random perturbation $\varepsilon t$is white noise

3.5.3. Moving Average Models

A moving average model employs historical forecast mistakes in a regression-like model instead of historical values of the forecast variable in a regression.

The current value of a moving averaging process is the linear sum of one or more prior perturbations and the current disturbance. The order of the moving average shows the number of prior periods incorporated in the present value. A moving average is thus defined by an equation.

$$Q_t 1/4 \alpha_1 * \theta_t \alpha_{t1} \tag{5}$$

4. Results analysis with Discussion

Every response that was gathered from the surveys is input into the program. The data view is where the program, variables, or questions are initially entered. The pie chart shows the percentage of respondents. Moreover, 60% of respondents are interested in giving an interview.

About 34% respondents are partially interested in the interview, and 6% of respondents are not interested in a part of it. This frequency, which is utilised to identify the crucial component, is found from the different data entered into the software. The simulation parameters are listed in Table 1.

Table 1. Simulation parameters of the proposed model

Parameter	Value
Model Type	Hybrid ANN + ARIMA
ANN Hidden Layers	2
Neurons per Layer	[16, 8]
Activation Function	ReLU (hidden), Linear (output)
Learning Algorithm	Levenberg–Marquardt
Epochs	1500
Learning Rate	0.005
ARIMA Order (p, d, q)	(2, 1, 2)
Data Normalisation Technique	Min-Max Scaling (0 to 1)
Performance Metrics Used	MSE, MAE, MAPE, R^2

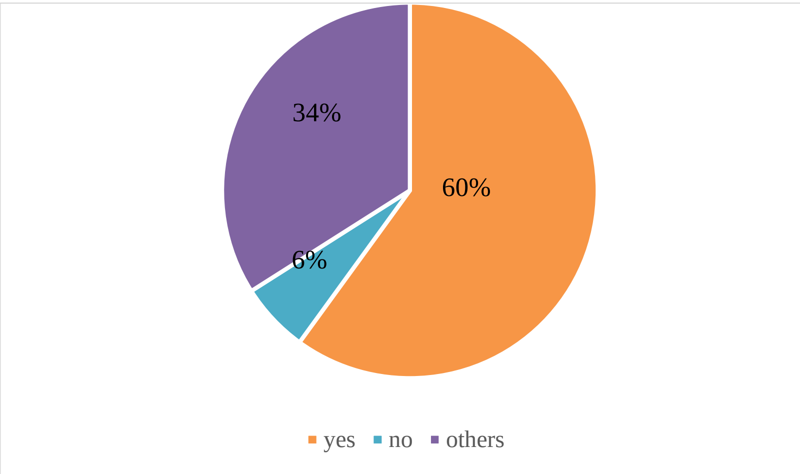

Fig. 5 Pie chart based on response

Table 2. Ranking factors and relative importance index

Category	Factors	RII (%)
Engineer	Raw material	24.52
	gross profit	86.25
	Labour Availability	72.15
	Size of contract	65.28
	Project location	56.2
	Type of project	89.15
	Material availability	36.2
Manufacturer	Types of clients	11.2
	Delay in payments	67.12
	Owner	66.25
	Expected Changes	78.25
	Experience of a consultant	74.1
	Cost estimation Accuracy	10.2
Contractor	Previous profit in similar projects	9.47
	Expected waste quantity	11.28
	Productivity of labour experience in similar old projects	7.54
External Factors	Economic stability	13.2
	Currency value	16.2
	Price fluctuation	181
	Changing government laws	22.25
	Availability of another project	24.2
	Level of competition	79.25
	Type of contract	69.2

4.1. Data Source and Sample Size

Project characteristics include surveying the client, engineer, manufacturer, contractor, skilled and unskilled labour and planning engineer. A survey was created and given to several organisations to gather information from the finished building projects in the delta district region of Tamil Nadu, India. The most important aspect of the survey is the owner's sector project classification and the project type based on the type of work completed.

4.2. Relative Importance Index

The Relative Importance Index (RII) was calculated in Table 1 to rank the 35 factors affecting the profit using the following equation.

$$RII = \frac{10R10+9R9+.....+1R1}{10(R10+R9+...R1)} \quad (1)$$

Where the numbers of respondents in each category are R10, R9, R8, R7, R6, R5, R4, R3, R2 R1, etc. With relative importance indices of 90.79%, 89.44%, 88.01%, 86.89%, and 86.37%, respectively, economic stability, cash flow, degree of difficulty, contract size, and contract type were the most crucial factors for determining the net profit ratio, according to an evaluation of the importance indices of each of the factors in Table 2.

With relative relevance indices of 2.85%, 2.10%, and 1.80%, respectively, delay penalties, safety regulations, and client experience were the least significant elements in determining the net profit ratio.

4.3. ANN Result by using MATLAB Software

The MATLAB trial and the transfer function, specifically the hyperbolic tangent function, or tensing in MATLAB, for the neurons in the hidden layers, were shown to produce better results and faster convergence during training and validation.

The work was carried out utilising MATLAB software with an i3 processor in order to estimate the best-fit probability distribution of cash flows, overdrafts, and profit and to minimise the uncertainty of activity costs.

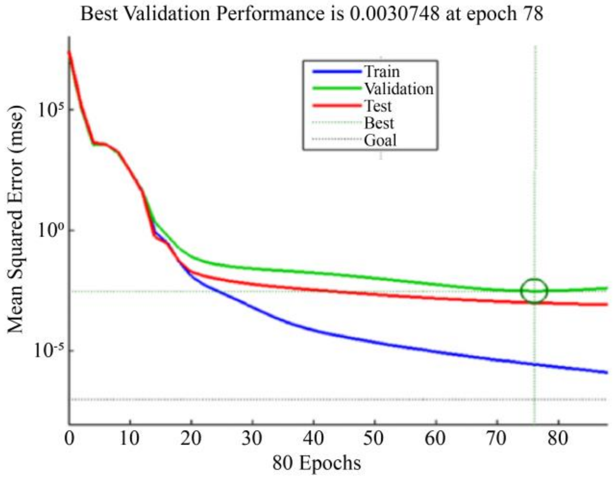

Fig. 6 ANN train and test result

In Figure 6, the ANN structure has the lowest mean square error (MSE) of any single hidden layer network structure in the validation data. The 5-9-1 model, which was created to predict the occurrence of disputes, has a relatively robust MAPD of 12.22417 percent and an acceptable MSE of ± 0.89 percent.

Mean Squared Error (MSE) is commonly calculated by summing the squared difference between predicted and actual values of data. Mean Absolute Error (MAE) is used to take the absolute difference between each predicted value and the corresponding actual value. Mean Absolute Percentage Error (MAPE) is computed to calculate the average of the absolute percentage of predicted and actual values for each data point.

Regression models, Mean Squared Error (MSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Adjusted R-Squared (R2) are also used to evaluate the profitability results. The models were obtained by altering the number of hidden layers and the number of neurons in each layer. The performance measures are listed in Table 3.

Table 3. Measures for the predictor ANN-ARIMA model validation

ARIMA Model	Performance Measure
Mean Squared Error (MSE)	$1/n \sum_{i=1}^{n} (A_i - P_i)^2$
Mean Absolute Error (MAE)	$1/n \sum_{i=1}^{n} \lvert A_i - P_i \rvert$
Mean Absolute Percentage Error (MAPE)	$\frac{1}{n} \sum \lvert \frac{P_i - A_i}{P_i} \rvert$
Adjusted R-Squared (R2)	$1 - \frac{\sum_{i=1}^{n}(A_i - P_i)^2}{\sum_{i=1}^{n}(A^{-}{}_i - A_i)^2}$

Table 4. Performance measures of methods

Measures	ANN	Time Series	ANN+ARIMA
MSE	0.22	0.13	0.09
MAE	0.11	0.455	0.155
MAPE	0.25	0.18	0.092
R^2	0.45	0.52	0.85

The ANN model produces more accurate results than the time series and regression models, as shown by their higher error values in Table 4 and Figure 7. In Mean Squared Error (MSE), the ANN value is 0.22 and the Time Series is 0.13, but the error metrics in ANN with ARIMA are lower at 0.09. The Mean Absolute Error (MAE) for the Time series is 0.455, and ANN is 0.11and the ANN with ARIMA is slightly higher than ANN (0.155). The value of ANN in Mean Absolute Percentage Error (MAPE) is 0.25, and the time series is 0.18.

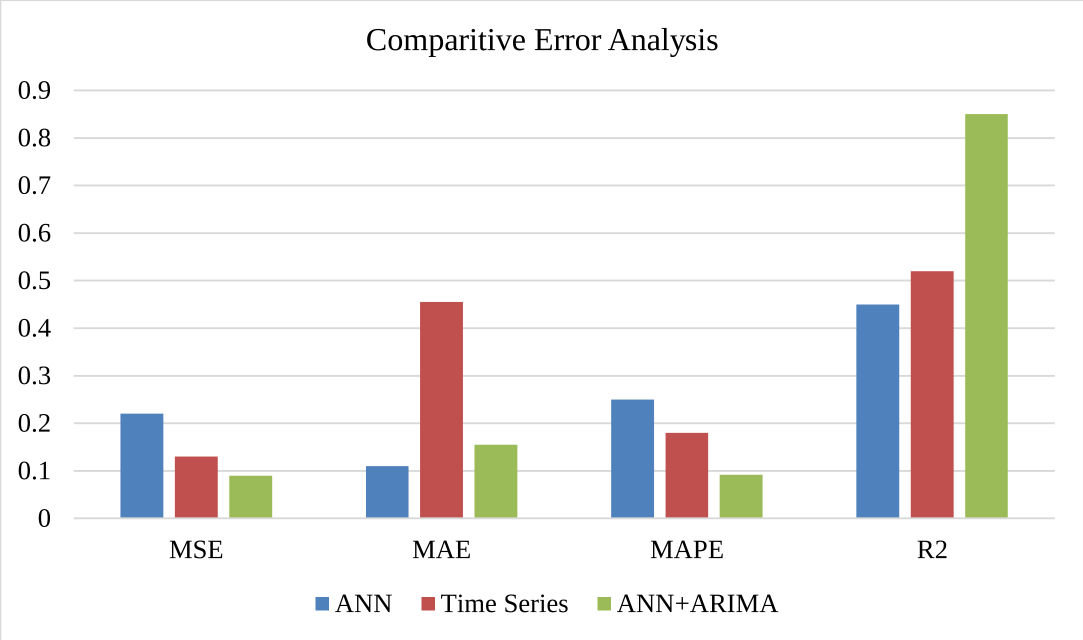

Fig. 7 Comparative error analysis

However, the error in the ANN with ARIMA is 0.092. In the Regression (R^2), the value of ANN is 0.45, the time series is 0.52, and the value of ANN with ARIMA is 0.85. However, because of their comparable MAE values, the Time series model is just as dependable as the ANN. With MAE and MAPE, R2 values are comparable to the ANN with the ARIMA model but superior to both in other error metrics. The ANN model provides the most reliable findings overall in this investigation.

Table 5. Performance measures of the ARIMA model

Models	MSE	MAE	MAPE	R^2
ARIMA (2,2,1)	3.34	2.22	2.51	1.89
ARIMA (2,2,2)	2.48	2.85	2.22	1.45
ARIMA (1,2,1)	3.55	2.66	2.45	1.85
ARIMA (1,2,2)	3.47	3.12	2.3	2.11

Interestingly, Table 5 shows that, when compared to the other measures, the two goodness metrics of the chosen ARIMA (2,2,1) have the lowest values. There is agreement between the two criteria in this work, even though MSE frequently favours higher-order ARIMAs.

Additionally, the ARIMA (2,2,2) was chosen by the accuracy measure MAE, but its result was extremely close to that of the ARIMA (2,2). Generally speaking, the best and most appropriate model depends on metrics of accuracy and model goodness of fit.

As previously stated, the final created model was presented to all ten example projects without the percentage of their profit ratio in Figure 8. After comparing the actual project percentages with the expected percentages, the absolute difference between the two was used to determine the discrepancies. To show that the proposed model can forecast the profit ratio, the absolute differences, which varied from -0.0315% to 0.043%, are deemed adequate. A questionnaire was created to determine the profit ratio for the various construction projects of important components, and the replies were examined.

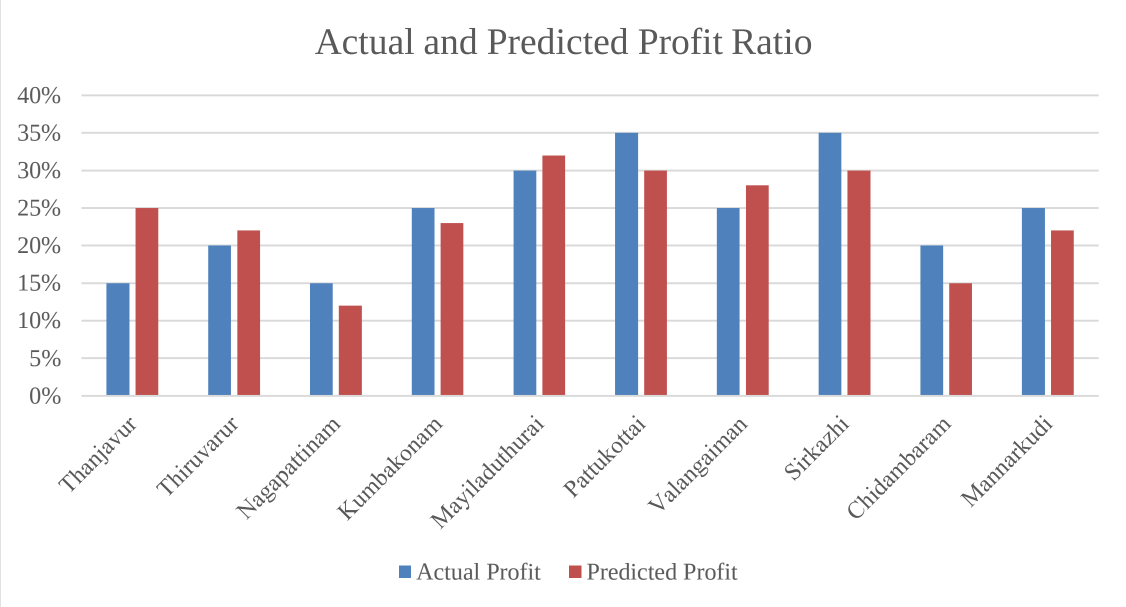

Fig. 8 Profit ratio analysis

Table 6. Comparison analysis of the conventional techniques

Author (Year)	Model / Technique	MSE	MAE	MAPE
Cheng et al. (2025) [16]	OMA-NN	0.18	0.21	0.11
Ye et al. (2019) [18]	PSO-BP Neural Network	0.20	0.25	0.14
El-Hazek et al. (2024) [19]	RII + Pareto + Statistical Model	0.26	0.29	0.18
Maya et al. (2023) [20]	ANN	0.22	0.24	0.15
Al-Gahtani et al. (2024) [22]	ANN + Logarithmic Smoothing	0.16	0.19	0.12
Foundation Pit Study (2024) [25]	LSTM-RNN-ANN	0.14	0.18	0.10
Proposed Model (2025)	ANN + ARIMA (Hybrid)	0.09	0.155	0.092

The comparison analysis of the conventional techniques is presented in Table 6. The graph in Figure 8 represents the analysis done to determine the discrepancy between the actual profit ratio and the expected profit ratio. As training goes on, the ANN model weights will be in the Delta district of Tamil Nadu. The projects were taken from Thanjavur and Thiruvarur. Mayiladuthurai may get the predicted profit ratio compared to the expected profit based on the analysis of ANN and ARIMA modelling. But in the remaining area, projects like Nagapattinam, Kumbakonam, Sirkazhi, Valangaiman, Chidambaram, and Mannarkudi had only gotten the actual profit as per the standard ratio, before they got into previous projects. Because it was continuously adjusted until the estimated outputs' inaccuracy converged to a manageable level, it was a reason for being unable to get the predicted profit ratio.

5. Conclusion

The purpose of this study was to identify the key factors impacting the project disagreement criterion in order to develop a project profitability prediction model. Using the RII, a questionnaire was created, and responses were examined to assess each factor's significance. According to the study, recurrent networks, more especially, ANN with ARIMA networks would increase accuracy even further by discovering that profitability performance varies across several project parameters and that profit margins change over time. To effectively anticipate profit margins, these insights require that project-specific knowledge be taken into account while training machine learning algorithms.

Lastly, using the altered training data, the ANN model was created. The findings showed that, when using standardised data and the logarithmic method suggested by ARIMA, the ANN model yields MSE, MAE, R2, and MAPE values of 2.22, 0.23, 1.45, and 2.58. Top management will be able to forecast the ideal profit ratio with the aid of this model.

By using an ANN and an ARIMA model, we can make a role, and the value of the time series depends on the ANN. Comparatively, the ANN with the ARIMA model value reduces the error and gives more accuracy in analysing the models by predicting profits and costs using deep learning algorithms and expanding the model to include additional building materials and developing countries.

Future Research

The research identified that profitability performance varies across several project parameters and that profit margins change over time. Here, the ANN and ARIMA models show how to minimise errors and provide clarity to improve the profit ratio. To effectively anticipate profit margins, these insights require that project-specific knowledge be taken into account while training machine learning algorithms.

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