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PREDICTING THE INDIRECT COST OF CONSTRUCTION PROJECTS IN EGYPT: AN ARTIFICIAL NEURAL NETWORK APPROACH

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ABSTRACT: Precise cost estimation is fundamental to effective construction project management. Site overhead costs, which constitute a significant portion of project expenses, is a critical area that needs to be efficiently managed and controlled in order to consequently increase the likelihood of success in bids and improve the financial stability of companies. Therefore, the main objective of this research is to enhance the contractor's ability to accurately predict the site overhead costs of construction projects in Egypt through identifying and analyzing the key factors influencing site overheads in the Egyptian construction industry. The model's database was constructed by first identifying key factors influencing site overheads through a comprehensive literature review. These factors included project characteristics (type, location, duration, contract, total direct cost, client, company class) and macroeconomic indicators (inflation, interest, exchange rates).This study then proposes an ANN model developed using Python Programming Language to predict the site overheads as a percentage of the total direct cost, while incorporating both economic and non-economic variables. Cost data from 55 actual projects completed over the last 10 years were gathered to serve as a database for the training and testing phase of the ANN model, while 5 other projects were utilized to validate the model. The model had a MAE value of 2.75% for the training set and 3.9% for the testing set. For the validation set, the MAPE was 4.86%. Overall, the model offers a valuable tool for contractors to enhance cost estimation, improve decision-making and mitigate financial risks.

1. INTRODUCTION

The construction industry in Egypt, a major contributor to the nation's GDP (Mordor Intelligence, 2022), operates in a highly competitive environment characterized by complex challenges such as risk analysis, bidding, and cost management (Kulkarni et al., 2017). Despite its economic significance, the sector has faced disruptions due to economic and political instability, including the 2011 revolution and the 2016, 2022, 2024 currency devaluation (Idrees et al., 2019; Khedr et al., 2016). In this volatile landscape, precise cost estimation has become essential for construction companies to remain competitive and profitable (Idrees et al., 2019).

Project success hinges on effectively balancing the critical constraints of cost, time, and quality (Rezaian, 2011). However, cost overruns remain a significant concern, often stemming from inaccurate cost estimations (Cheng et al., 2010). To address the challenge of cost overruns, advanced estimation methodologies are essential (Enshassi et al., 2013). Artificial intelligence (AI) techniques, including Artificial

Neural Networks (ANN), have shown potential in enhancing construction management practices (Kulkarni et al., 2017).

While direct costs are relatively easier to estimate, overhead costs, specifically site overheads, present a significant challenge for construction companies (Hassouna et al., 2020). While crucial for bidding success and contractor profitability, project overhead estimation often receives less attention than direct cost estimation, resulting in approximations rather than precise calculations. This is partly due to the misconception that these costs constitute a minor portion of the overall contract sum. However, accurate estimation of project overheads is vital for ensuring project success and profitability (Chan and Pasquire, 2002). Accordingly, this research aims to address this critical gap by developing an Artificial Neural Network (ANN) model to predict site overhead costs as a percentage of total direct costs for construction projects in Egypt. This model will leverage historical data to enhance the accuracy of cost forecasting, enabling construction companies to better control costs, improve project profitability, and make more informed decisions regarding resource allocation.

2. LITERATURE REVIEW

2.1 Cost Estimation Fundamentals

Cost estimation, as defined by the Project Management Institute (2013), involves determining the financial resources required to complete project activities. In construction, costs encompass both direct and indirect components (AACE, 2017). Direct costs, directly attributable to specific project activities, primarily include materials, labor, equipment, and subcontractor expenses (AACE, 2017). Conversely, indirect costs (overheads) are incurred for general project support and cannot be directly assigned to individual activities. These costs, such as field administration, contractor fees, and site supervision, are typically allocated across all project activities (AACE, 2017).

2.2 Overhead Cost Categories

Construction industry literature generally categorizes overhead costs into two primary types: site overheads and general overheads (Bakr, 2018; Lesniak and Juszczyk, 2018; Patil and Bhangale, 2014). Site overheads encompass expenses directly related to on-site project execution, excluding direct costs. Examples include staff salaries, site safety measures, and equipment transportation (Bakr, 2018). In contrast, general overheads are incurred for overall business operations and are not directly associated with specific projects. These costs, such as office salaries and rent, are allocated across all projects within the company (Bakr, 2018; Lorman, 2014).

2.3 Factors Influencing Indirect Costs

Research has identified several factors significantly impacting indirect costs in the Egyptian construction sector. ElSawy et al. (2010) highlighted project duration, type, total contract value, location, and site preparation needs as key influences. Bakr (2018) further emphasized contract type, company class, project duration, location, direct costs, and company ownership (public/private) for residential projects. Idrees and Elseddawy (2023) expanded on this by including inflation rate as an additional factor. Similarly, Othman (2020) considered these factors along with client type. Al-Tawal et al. (2020) suggested that incorporating macroeconomic indicators like inflation, interest rates, and exchange rates could enhance model reliability.

Model parameters were selected through a rigorous literature review identifying 40 potential factors influencing indirect construction costs. To prioritize the most significant, a frequency analysis and the Pareto principle were applied, focusing on the 20% of factors most frequently cited by scholars. This data-driven approach ensured the inclusion of highly influential parameters. These factors are shown in Table 1.

Each factor influences the site overheads percentage in a different way. Different project types necessitate varying levels of coordination, supervision, safety measures, and transportation, impacting overhead costs (Chan, 2012; ElSawy et al., 2010). Regarding project location, urban projects often incur higher overhead costs due to increased transportation costs, temporary facilities, and security requirements compared to rural projects (ElSawy et al., 2010; Chan, 2012). Additionally, longer project durations generally lead to increased overhead costs, particularly those related to site management and supervision (ElSawy et al., 2010; Hesami and Lavasani, 2014). Concerning contract type, the most commonly used in Egyptian construction projects are lump-sum, unit price and cost plus contracts (Idrees and Elseddawy, 2023; ElSawy et al., 2010; Bakr, 2018). Lump-sum contracts may exhibit higher overhead costs due to the increased risk of cost overruns (Bakr et al., 2018). For the project size, it can be noted that larger projects typically incur higher overhead costs due to increased resource requirements and management complexities (ElSawy et al., 2010). Regarding the class of contracting company, researchers stated that higher-grade companies often have larger workforces and more sophisticated equipment, leading to higher overhead costs (ElSawy et al., 2010; Hesami and Lavasani, 2014). Regarding the client type, projects undertaken for public entities may exhibit lower overhead costs compared to those for private clients due to potentially less stringent quality and management requirements (ElSawy et al., 2010). Lastly, researchers have concluded that macroeconomic indicators are highly influential as fluctuations in inflation, interest rates, and exchange rates significantly impact construction costs and, consequently, overhead expenses (Warsame, 2006; Puci et al., 2023; Fan et al., 2010).

Table 1: Factors to be used as model inputs.

Factors
Project Type
Project Location
Project Duration
Contract Type
Project Size (Total Contract Amount / Total Direct Cost)
Client Type
Class of Contracting Company
Macroeconomic indicators (inflation rate, interest rate, exchange rate)

2.4 Artificial Neural Networks and Their Application in Egypt

Artificial Neural Networks (ANNs) are computational models inspired by the human brain, comprising interconnected processing units ("neurons") that collectively solve problems (Dastres and Soori, 2021). ANNs have been employed in construction management since the early 1990s (Lesniak and Juszczyk, 2018) and have shown promise in various applications within the field (Dikmen and Sonmez, 2011). Several studies have utilized ANNs for indirect cost estimation in Egyptian construction. ElSawy et al. (2011) developed an ANN model to predict site overheads using data from 52 projects between 2002 and 2009, achieving 80% accuracy. Bakr (2018) developed a similar model for residential projects using data from 55 projects between 2011 and 2018, achieving 83.3% accuracy. Othman (2020) developed an ANN model for various project types using data from 40 projects, achieving an R-squared value of 0.888. More recently, Idrees and Elseddawy (2023) developed an ANN model for commercial projects using data from 55 projects between 2017 and 2023, achieving 84% accuracy.

2.5 Research Gap

Existing research in Egypt primarily focuses on internal project factors, often neglecting the influence of external macroeconomic factors (inflation, interest rates, exchange rates). Additionally, many studies utilize limited datasets, focusing on specific project types and older data, which may not accurately reflect current market conditions.

3. RESEARCH OBJECTIVES

The main objective of this research is to enhance the contractor's ability to accurately predict the percentage of site overheads in construction projects in Egypt through the following:

- identifying and analyzing the key factors influencing site overheads in the Egyptian construction industry.
- developing a robust dataset containing historical cost data of projects executed in the past 10 years.
- developing an ANN model that accurately predicts the total percentage of site overheads for construction projects in Egypt, incorporating both economic and non-economic variables.

4. RESEARCH METHODOLOGY

The research methodology commenced with a comprehensive literature review to identify key factors influencing site overheads and assess the suitability of ANNs for this application. Data was then collected through a structured questionnaire and analyzed to identify significant predictors and address potential biases. An ANN model was developed using Python on Google Colaboratory, encompassing data preprocessing, architecture selection, and training. Finally, the model was rigorously validated using a separate dataset of five construction projects to evaluate its predictive accuracy and reliability.

4.1 Site Overhead Cost Data Collection

Data was collected from industry experts using a structured data collection form. This questionnaire captured respondent information, detailed project characteristics and critical cost data (total contract amount, direct and indirect costs).

4.2 Macroeconomic Data Collection

Data for the three primary macroeconomic indicators impacting indirect costs (as indicated from the literature review) – inflation rate, interest rate, and the USD-EGP exchange rate – were obtained from the Central Bank of Egypt's online database. This database provided monthly rates for each indicator over the past ten years.

4.3 Sample Size

The number projects collected during the data collection phase was 55 projects. To ensure adequate sample size, a sample size calculation was performed using the Equation 1 (Israel, 1992).

$$n = (\frac{z * \sigma}{E})^2 \quad \textbf{(1)}$$

For this research, the desired confidence level considered was 90% and the margin of error was 10%. The standard deviation of site overheads was estimated to be 0.0443, which was derived from combining Chao's (2008) findings (0.0428) with the standard deviation observed in this study's preliminary analysis (0.0457). Accordingly, the output was 53 projects. The actual sample size of 55 projects exceeded this value, providing sufficient data for robust analysis.

4.4 ANN Guide

4.4.1 Reasoning for the Selection of ANN

Given the intricate nature of predicting site overheads and the absence of a linear relationship between the variables, ANNs were selected as the most appropriate machine learning technique for this research. ANNs, renowned for their ability to handle complex, nonlinear relationships and large datasets, are well-suited for the models developed in this research. Their capacity to learn from historical data and identify complex patterns, and adapt to changing conditions makes them particularly valuable in this context. Additionally, the backpropagation algorithm, a core component of ANNs, enables them to effectively learn from data, refine their predictions and generate outputs with high levels of accuracy (Nielsen, 2015).

4.4.2 Model Design Steps

The model development process followed a structured approach, encompassing data preprocessing, architecture design, training and testing.

- **Data Preprocessing:** Categorical variables (project type, location, etc.) were encoded using label encoding to ensure compatibility with the ANN (Kshirsagar & Rathod, 2012; Potdar et al., 2017). Numerical data was normalized using min-max scaling to prevent bias towards variables with larger scales (Heaton, 2017).
- **Architecture Design:** The ANN architecture comprised an input layer representing the selected input variables, one or more hidden layers to capture complex relationships, and an output layer predicting the site overhead percentage. The number of hidden layers and neurons was determined through iterative experimentation. Various activation functions (ReLU, sigmoid, tanh) were evaluated to optimize model performance (Heaton, 2017; Srinivasan et al., 2019).
- **Training and Validation:** The backpropagation algorithm was employed to train the network, minimizing the root mean squared error (RMSE) between predicted and actual values (ElSawy et al., 2011; Idrees et al., 2023). Model performance was assessed using metrics such as mean absolute error (MAE) and mean squared error (MSE).
- **Model Testing:** The trained model was rigorously tested on a separate dataset of projects not used in training. Absolute percentage error was calculated to evaluate the model's predictive accuracy and reliability.

5. DATA COLLECTION AND ANALYSIS

5.1 Analysis of Questionnaire Respondents

Data for this study was collected through a data collection form distributed to 64 experienced cost engineers working in reputable contracting firms in Egypt, with a response rate of 86% (55 responses). All respondents were employed by Grade A contracting companies only. As shown in Figure 1, the respondents exhibited a diverse range of experience levels. This diverse professional background provided valuable insights from individuals with varying levels of expertise and industry knowledge.

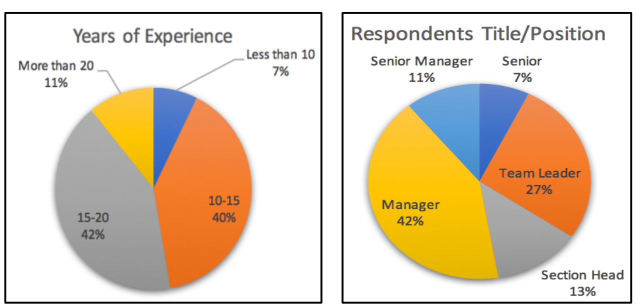

Figure 1: Respondents' analysis.

5.2 Comparative Analysis of Data Collected

The data set consists of 55 construction projects executed in Egypt between 2018 and 2024. As illustrated in Figure 2, the dataset encompasses a diverse range of projects. In addition, this section presents a comparative analysis of the collected, as shown in Figure 3. The analysis aims to investigate the influence of key factors, identified in the literature review, on site overhead percentages. This analysis will help determine the factors with the most significant and least significant impacts on site overhead costs.

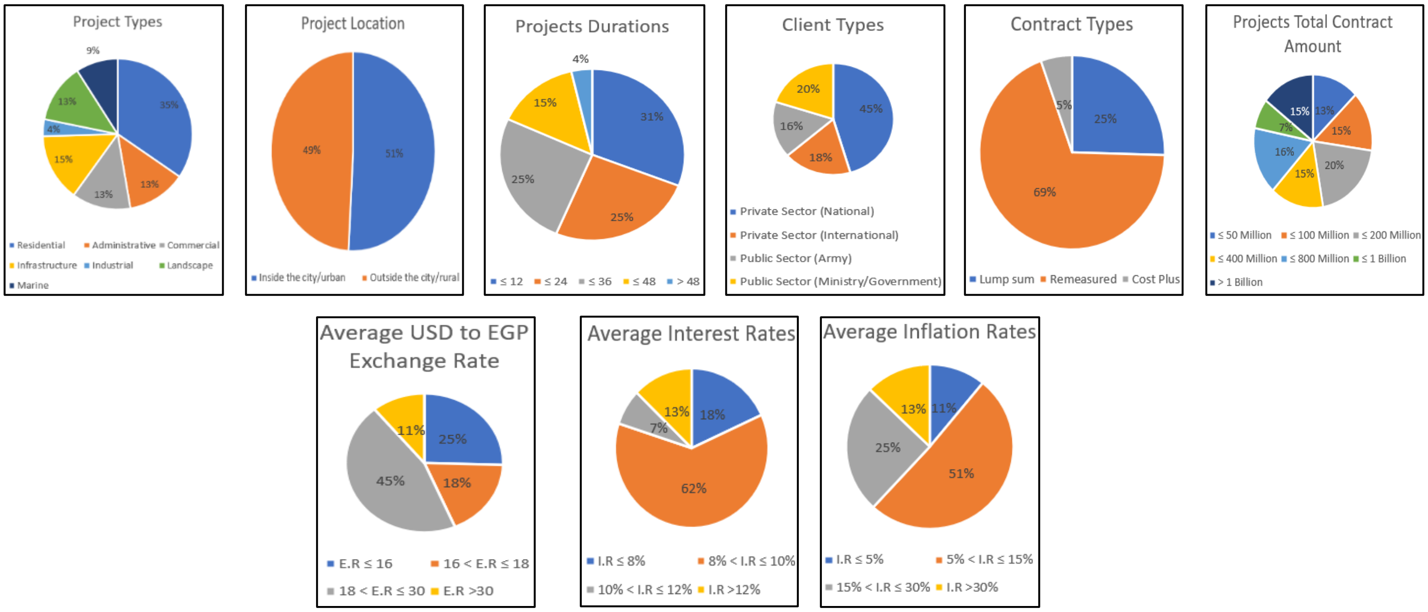

Figure 2: Data Set Diversity

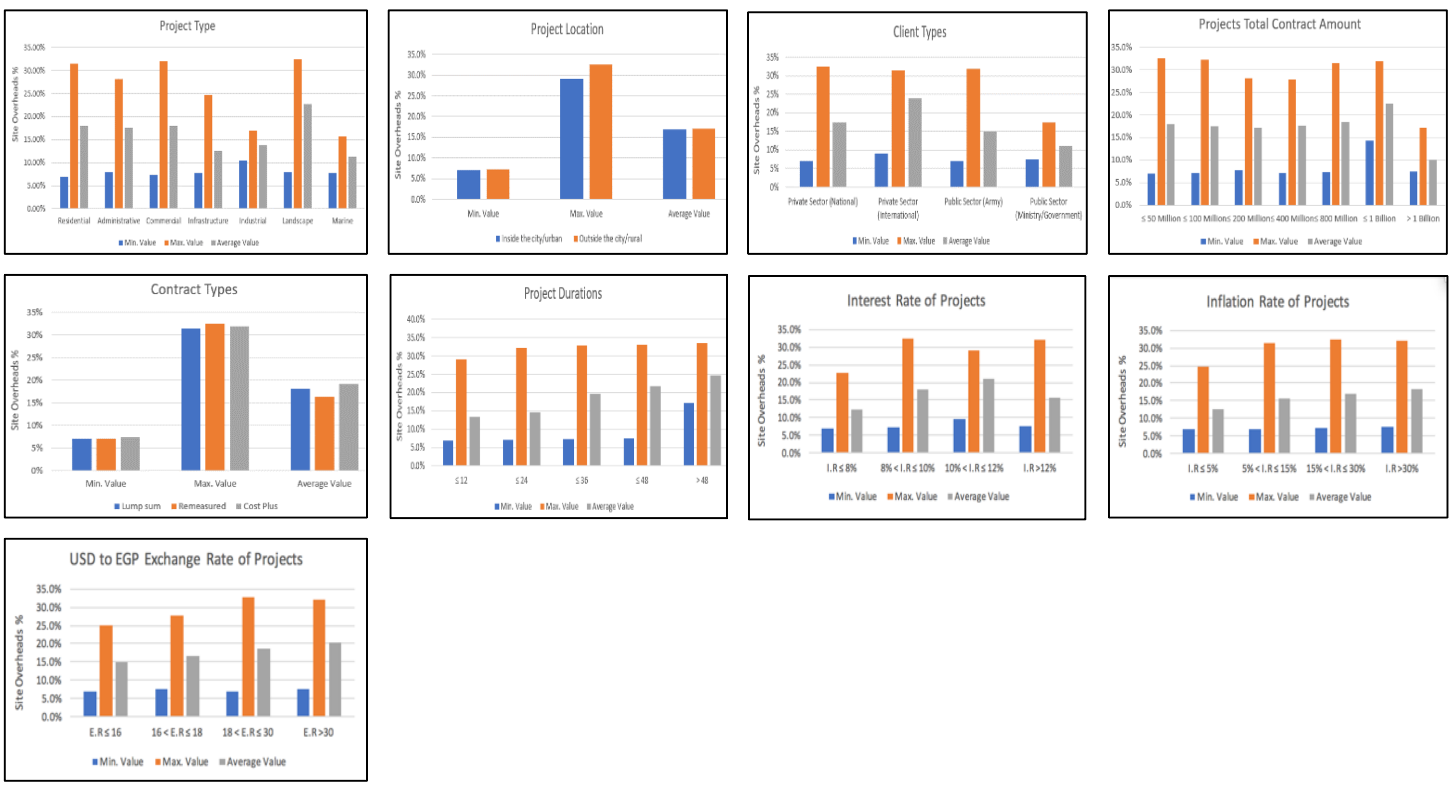

Figure 3: Comparative Analysis of Factors

Comparative analysis reveals key trends in site overhead percentages. Landscape, commercial, residential, and administrative projects exhibit higher average site overhead percentages compared to marine projects. Projects located outside the city generally incur higher site overhead costs. A direct correlation is observed between project duration and site overhead percentage, as well as between project contract amount and site overhead percentage. In terms of client type, international private sector projects tend to have higher site overhead percentages compared to public sector (ministry/government) projects. Re-measured contracts exhibit higher overhead percentages compared to lump-sum contracts. Furthermore, the analysis indicates a direct relationship between site overhead percentages and increases in inflation rates, interest rates, and the USD-EGP exchange rate.

5.3. Pearson and Spearman Correlation Analysis

To assess the correlation between the factors and the site overheads percentage and to determine which factors have the highest impact and which factors do not have a major impact, correlations tests like Pearson and Spearman correlation tests must be done. These tests were done on Microsoft Excel using excel add-in called StatTools. As shown in Tables 2 and 3, the factor that has the highest impact on site overheads percentage is project duration, followed by total direct cost. In fact, the project duration has a positive linear relationship with the site overheads percentage while the total direct cost has a negative linear relationship. The rest of the factors also have a considerable impact on the site overheads percentage.

Table 2: Pearson Correlation Test Between Factors and Site Overheads Percentage

	Site Overheads %
Linear Correlation Table	Data Set #1
Project Type	-0.101
Project Location	0.114
Project Duration (months)	0.402
Client Type	-0.311
Contract Type	-0.145
Avg. Interest Rate	0.107
Avg. Inflation Rate	-0.127
Avg. USD to EGP Exchange Rate	-0.274
Total Direct Cost	-0.315
Site Overheads %	1.000

Table 3: Spearman Correlation Test Between Factors and Site Overheads Percentage

	Site Overheads %
Rank-Order Correlation Table	Data Set #1
Project Type	-0.107
Project Location	0.114
Project Duration (months)	0.401
Client Type	-0.262
Contract Type	-0.132
Avg. Interest Rate	0.148
Avg. Inflation Rate	-0.107
Avg. USD to EGP Exchange Rate	-0.189
Total Direct Cost	-0.262
Site Overheads %	1.000

6. MODEL DEVELOPMENT

6.1 Software Used

Python, a versatile and user-friendly programming language with extensive libraries was chosen for model development due to its robust capabilities in predictive data analytics (Jawahar, 2023). Google Colaboratory, a free cloud-based service, was leveraged as the development environment, eliminating the need for local software installations and providing access to powerful computing resources (Naik, 2022). This cloud-based platform facilitates seamless code execution within a web browser, enhancing accessibility and enabling efficient model development.

6.2 Model Development Steps

The following steps were done in an iterative manner to achieve optimal model performance. Firstly, a dataset comprising 55 construction projects executed in Egypt between 2018 and 2024 was compiled in Microsoft Excel. This dataset included 10 variables: 9 input variables and 1 output variable (site overheads percentage). Then**,** data preprocessing was performed which involved coding categorical variables and normalizing numerical data using min-max scaling. Then, the data was split into training and testing tests as follows: 80% for training and 20% for testing. Then, the most optimum model architecture was defined after a trial and error process. Model 1 architecture consisted of 9 input neurons and 1 output layer representing the percentage of site overhead from the total direct cost of a construction project. The model had 2 hidden layers. The first hidden layer contains 64 neurons and ReLU (Rectified Linear Unit) activation function. The second hidden layer contains 32 neurons and ReLU activation function. After that, the model was trained on the training data for 100 epochs, using back-propagation, which is an iterative learning technique that adjusts network weights based on the root mean squared error (RMSE) between predicted and actual outputs, continuing until the RMSE converges to an acceptable level. Subsequently, the model's performance was evaluated on the entire dataset using metrics such as Mean Absolute Error (MAE) and Mean Squared Error (MSE). The model was then evaluated on a separate, unseen dataset, again using MAE and MSE.

6.3 RESULTS AND DISCUSSION

During the 100 training epochs, the model demonstrated consistent improvement in accuracy, with the MSE decreasing from 0.0135 to 0.0013 and MAE reducing from 8.79% to 2.75%. While the model exhibited slightly higher MSE and MAE values on the testing set (0.0031 MSE and 3.9% MAE), indicating potential overfitting, the difference was considered acceptable. To further assess model generalization, a validation phase was conducted using a separate dataset of unseen projects, shown in Table 4.

Table 4. Model Validation Set

Project No.	Project Type	Project Location	Project Duration (months)	Client Type	Contract Type	Avg. Interest Rate	Avg. Inflation Rate	Avg. USD to EGP Exchange Rate	Total Direct Cost (EGP)
1	Marine	outside the city/rural	27	Public Sector (Ministry/Government)	Remeasured	12.5%	21.1%	17.75	97,900,000.00
2	Administrative	inside the city/urban	30	Private Sector (International)	Lump Sum	8.0%	11.2%	18.65	102,280,753.80
3	Residential	inside the city/urban	45	Private Sector (International)	Lump Sum	8.5%	13.2%	19.55	569,683,416.83
4	Commercial	outside the city/rural	40	Private Sector (National)	Remeasured	8.9%	16.1%	21.56	423,941,649.60
5	Infrastructure	outside the city/rural	14	Public Sector (Ministry/Government)	Lump Sum	12.2%	35.1%	30.60	1,201,857,757.21

The validation results, as shown in Table 5, demonstrate high accuracy with all five projects exhibiting absolute percentage errors within 10%. Project 2 achieved the lowest error at 0.53%. The mean absolute percentage error across the validation set was 4.86%. In addition, Figure 4 illustrates the relationship between predicted and actual site overhead percentages, demonstrating a strong correlation with an R-squared value of 0.979.

Table 5. Validation Results

Project No.	Model's Predicted Value	Actual Value	Absolute Percentage Error
1	11.80%	12.69%	7.01%
2	24.46%	26.10%	6.28%
3	28.69%	28.54%	0.53%
4	26.30%	24.54%	7.17%
5	9.03%	8.74%	3.32%

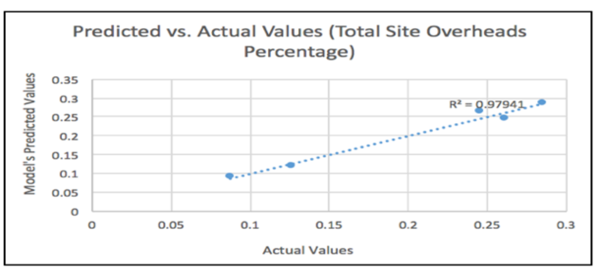

Figure 4. Predicted vs. Actual Values for Validation Results

7. CONCLUSION

The research successfully developed an Artificial Neural Network (ANN) model capable of accurately predicting the total percentage of site overheads in Egyptian construction projects. This model, utilizing nine input parameters encompassing project characteristics and macroeconomic indicators, demonstrated a strong predictive capability. Specifically, with its architecture of two hidden layers (64 and 32 neurons with ReLU activation), achieved a Mean Absolute Error (MAE) of 2.75% on the training dataset and 3.90% on the testing dataset. Furthermore, when assessed against a previously unseen validation dataset, the model yielded a Mean Absolute Percentage Error (MAPE) of 4.86%. These results indicate that Model 1 effectively learned the complex relationships between the input factors and the overall site overhead percentage.

Consequently, it can be considered a valuable tool for contractors in the Egyptian construction industry to enhance their cost estimation accuracy. By providing a reliable prediction of the total site overhead percentage, the model contributes to improved project budgeting and financial planning, ultimately aiding in more efficient project management.

To extend the applicability of this research in other countries, future work should prioritize identifying the most impactful factors influencing indirect construction costs within the target country. Subsequently, a comprehensive database relevant to that specific context needs to be established. While the general principles of designing, training, and validating an ANN model will remain consistent, the model architecture may require tuning to suit the new dataset's characteristics. Rigorous validation using local data is essential to ensure the adapted model's accuracy. This systematic approach, focusing on understanding local cost drivers and building a relevant dataset, will pave the way for a reliable and context-aware indirect cost prediction model in diverse international construction environments.

8. RESEARCH LIMITATIONS

- The study's primary limitation lies in the reliance on expert-provided data, which may introduce subjectivity.
- The focus on the Egyptian construction industry limits the generalizability of findings to other regions.
- The model's accuracy might be influenced by the availability and quality of data, as well as the complexity of the construction projects included in the dataset.
- This research dealt with category A companies only and thus cannot be generalized to projects relating to other categories.
- The dataset contained projects completed between 2018 and 2024, potentially hindering the model's ability to capture long-term economic patterns and trends

9. RECOMMENDATIONS FOR FUTURE WORK

- Developing a user-friendly interface (web-based application or software tool) that allows users to input project data and receive predictions without requiring technical expertise.
- Exploring the incorporation of additional factors such as project complexity and schedule constraints (including fast-tracking) into the ANN models.
- Expanding the dataset to include projects from different regions to enhance the model's generalizability.
- Expanding the dataset to include more projects in order to improve the accuracy of the outputs.
- Investigating the integration of other machine learning techniques is recommended to assess if there are other techniques that lead to higher accuracy.
- Enhancing the model's ability to detect economic patterns over time, it’s recommended to extend the study period and develop a dataset encompassing projects from older time periods

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