Using an Artificial Neural Network to Predict Construction Materials Prices in Khartoum State

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Abstract - *As a result of the construction industry's large expenditure, effective construction cost had become necessary. In order to estimate the expenses of building materials in Khartoum State, it is necessary to evaluate and determine whether ANNs is a viable instrument. The aim of this study is to evaluate the accuracy of artificial neural networks (ANNs) to calculate selected building materials prices in construction projects in Khartoum to decide ANNs ought to be used in the building sector. Four representative building projects across Khartoum State were selected, and the selected building materials expenses of those projects were then calculated. This information was gathered, loaded into MATLAB, and ANNs was created using the descriptive attributes as inputs and the corresponding building materials costs as the target output. The neural network then adjusted itself to try and predict the cost of the materials using the inputs that were provided. The cost created by the artificial neural network was compared to the actual cost after that. When the Neural Network outputs were compared to the real cost, it was discovered that there were absolute errors of 13.6%, 0, 2×10^{-6} %, and 10^{-9} % for each project., the maximum absolute inaccuracy stated is 1.73%, and the mean absolute percentage error is 0.44%. The authors advocate using an Artificial Neural Network to estimate building costs and urge its development with a wider scope and larger sample size.*

Key Words: ANN, Costs, Building Materials, MATLAB, Khartoum.

1. INTRODUCTION

Due to of the construction industry's significant spending, effective building cost management and/or quantity surveying became essential issue. This occurs to ensure that a building project's resources are used to their maximum potential. Increasing cost performance is the fundamental objective of management for any building project, consequently the cost component typically takes priority [2].

A construction project's performance has a high correlation with the capability to efficiently estimate spending, manage costs, and complete on time. [3][4] Mentioned that, to estimate material costs, a quantity surveyors must employ the greatest tools available. Due to the irregular nature of Sudanese market pricing, one of the challenges encountered by this research is that cost assessment in Sudan is often done through internal cost analysis. A procurement issue involving thoroughly documented preceding work to research and evaluate the pre- and post-execution costs of construction projects is present.

Prices of materials may alter over the period of the construction project due to Sudan's irregular changes in hard currency exchange rates and the bank's lack of funds. The accuracy of the estimate by the project's completion date may be affected by these price changes.

This study seeks to examine and determine whether an ANN is a useful tool for evaluating building project expenses in Khartoum State, Sudan. A further goal of the study is to decide whether artificial neural networks deserve to be used in the building sector.

2. LITERATURE REVIEW

Numerous studies have been conducted on the issue of estimating construction costs using deep learning techniques. [3] Attempted to forecast the price of communication towers in Iraq using a mathematical model based on a multifactor linear regression technique. In this study, the author argued that the Multifactor Linear Regression Technique (MLR), a powerful mathematical tool for demonstrating the engineering interaction between dependent and independent variables, constituted the most effective forecasting model. The study concluded that (MLR) outperforms more traditional methods for predicting the costs of communication tower constructions, which are less specific and prone to ambiguity. 90.1% accuracy was achieved in terms of cost estimation [5].

According to [3], deep machine learning algorithms can provide high levels of accuracy and a decent level of confidence when used in prospective tower construction projects. Nevertheless, this project would accomplish its objectives through the usage of artificial neural networks (ANN). The study included data from a variety of construction companies [6]. The study hypothesized that the variables investigated would have a significant impact on the ANN's overall performance.

In an additional analysis, 501 project datasets from 2005 to 2015 were collected [7]. The overall costs for twenty-five construction-related activities were collected. For the purposes of this study, it has been determined that using two hidden nodes and the sigmoid activation function for hidden and output layers resulted in the lowest possible testing and training errors as well as the maximum correlation in the cost estimation model. The correlation results had an accuracy of 94.91%, a precision of 100%, and a margin of error of 5.18%.

The performance was rated as extremely good for predicting building costs [7].

This study includes a greater number of inputs. Increasing the amount of training and inputs often leads to improved accuracy. However, the majority of these inputs are typically unavailable early in the lifecycle of projects. Although these algorithms are highly accurate, their usability degrades.

As an illustration investigate [8], which used only eight inputs or features to predict building costs. These parameters were chosen after careful analysis of the experimental data. The analysis conclusions revealed that the eight selected factors were "predominant cost drivers." As a result, they were chosen to design and train the network study. Other differences include using a sample size of thirty sites, providing construction cost per square meter rather than total construction cost, and focusing exclusively on multistory residential complexes. The study acknowledged the significance of more inputs and found that integrating more inputs may improve performance. Despite this fault, the formed neural network achieved an average accuracy of 93% over six samples.

The study discovered that the number of examples is strongly correlated with the neural network's performance in forecasting building expenses, resulting in a reduction in prediction error. "The necessity for specific project data, uncertainty about project development, changes in some design parameters, etc." have been highlighted as key disadvantages of traditional cost estimates.

[8][9] Used 91 surveys to identify the input variables. However, only 19 datasets were utilized for the ANN's training and validation. This study focuses entirely on residential apartment buildings, but it also examines the neighborhood and its concerns. It argues that lately there has not been much effort put into deploying neural networks in poor countries where construction is under threat owing to fluctuations in direct costs. In order to accurately anticipate building expenses, relevant strategies were sought in this study. Other economic issues were briefly discussed in the study, with a focus on the way the economy influences construction growth and capabilities.

Despite the challenges of inflating prices to match the ANN and the data set's modest size, the produced model regularly produced a Mean Absolute Percentage Error (MAPE) less than the permitted 10%. This study discovered that even if the ANN model had not been thoroughly tested, academics and practitioners might still profit from it. The study also noted that the model may be enhanced by upgrading the weight matrix with more data from completed projects. It also realized that additional input variables are necessary to improve the prediction of the neural network [9].

3. MATERIAL AND METHOD

This research set out to obtain a minimum of four sample projects that have been planned and built in Sudan inside its capital state of Khartoum in order to begin an evaluation of construction projects in Khartoum, Sudan. Once obtained, the writers conducted an exact quantity survey on the example projects. The four projects were multi-story residential buildings made of reinforced cement concrete. To avoid having results that varied greatly and made our analysis uncertain, we chose one style of construction in one sector. Additionally, it helped the research become more focused. The below flowchart illustrate the research process:

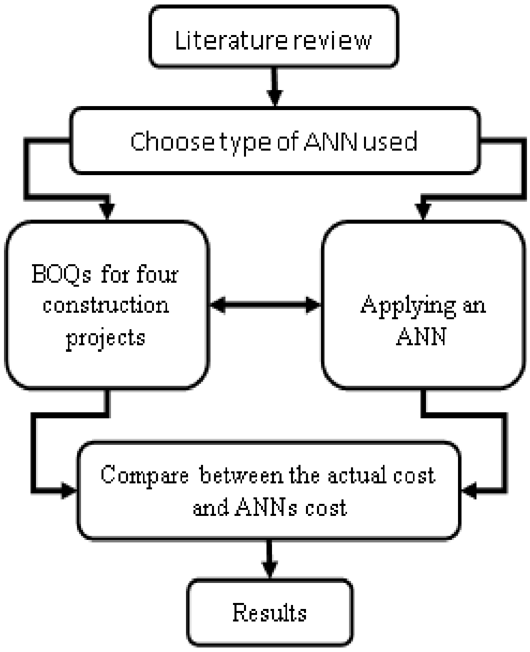

Chart -1: Research flowchart process

3.1 Creating bill of quantities (BOQ)

BOQ was created in Excel, and the total overall construction costs of the projects were estimated upon project conclusion. All material, labor, and equipment costs related with the projects are included in the total overall construction costs. The outcomes are shown in the table below:

Table -1: Total Construction Costs

Project	Total Construction Cost (SDGs)
G+1	61,645,361.00
G+2A	68,958,809.00
G+2B	53,254,006.00
G+3	96,555,559.00

3.2 Creating ANNs and Importing Quantitative Data

Because of its familiarity and reputation in the creation of Neural Networks, MATLAB was chosen for the usage of generating an ANN.

The descriptions that were used to determine the inputs the estimated total overall construction costs that determined the target outputs of the neural network for each multi-story building, namely Ground + 1 floor (G+1), the first Ground + 2 floors building (G+2A), the second Ground + 2 floors building (G+2B), and the final building Ground + 3 floors (G+3)

As previously stated in this chapter, when using data in this manner, MATLAB does not function as intended. As a result, it was modified in order to be compatible, as shown in the table below:

Table -2: G+3 Quantitative Inputs

Description	Amount			
	G+1	G+2 A	G+2 B	G+3
Reinforcement Bars (tons)	31.7	42.37	27.17	62.88
Stirrup Bars (tons)	1.95	1.27	1.39	1.47
Cement (tons)	157.51	178.63	140.14	229.61
Fine Aggregate (m3)	374.27	410.42	326.82	519.85
Coarse Aggregate (m^3)	284.48	319.18	249.61	412.01
Bricks (unit)	189398	208967	166800	243212

Table - 3: Target Outputs

Project	Total Construction Cost (SDGs)
G+1	61,645,361.00
G+2A	68,958,809.00
G+2B	53,254,006.00
G+3	96,555,559.00

After compiling the necessary data, it was imported into MATLAB's workspace. The Neural Network/Data Manager, also known as the Neural Network Tool, which can be accessed by typing "nntool" into the command window, may then simply import them. Next, select Import. The prompt will then allocate the variables into the chosen destination within the neural network data manager after you assign the Input variable you added to the workspace to the Input Data destination and click Import, as well as the Target Outputs variable you selected to the Target Data destination and clicked Import.

4. RESULTS

The outputs for the quantitative neural network that was created are shown in the following Table:

Table - 4: Quantitative Neural Network Outputs

Project	Total Construction Cost (SDGs)
G+1	53,254,229.74
G+2A	68,958,809.00
G+2B	53,254,016.97
G+3	96,555,558,99

The maximum error was found to be 13.6% in the quantitative assessment. The mean absolute percentage error for the quantitative neural network is 3.4%. These percentages meet the study's goals and show that ANN may be a useful tool for cost estimation of residential construction projects, particularly in the early stages of the project.

This is owing to the Neural Network outperformed previous background research, which found that the error in estimating building project expenses in the early phases varied from -30% to +50% and -25% to +50%, respectively.

These values given by the ANN are compared to the actual estimated total construction cost in the following table:

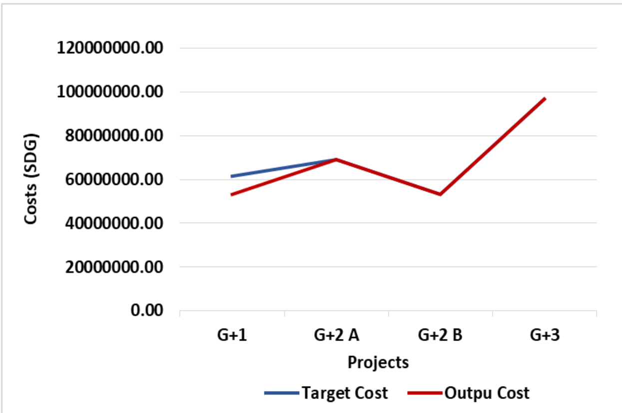

Fig -1: Comparison between Quantitative Target & Output Cost

These results were obtained after seven attempts to train the neural network. Because our study only included four example projects, only one could be validated and another examined. As a result, R has no value in their respective plots, as seen in Figures 3 and 5. R = NaN (Not a number). If the plot contained all of the projects, a regression relationship might be established. There is a very strong linear regression between the projects in the quantitative assessment, with an R-value of 0.98061. This substantial correlation in quantitative assessment can be attributed to the tuning of the weights in biases in neural network training, which was accomplished using random weight initialization and supervised training.

The regressions of the iterations used are shown in the following figures:

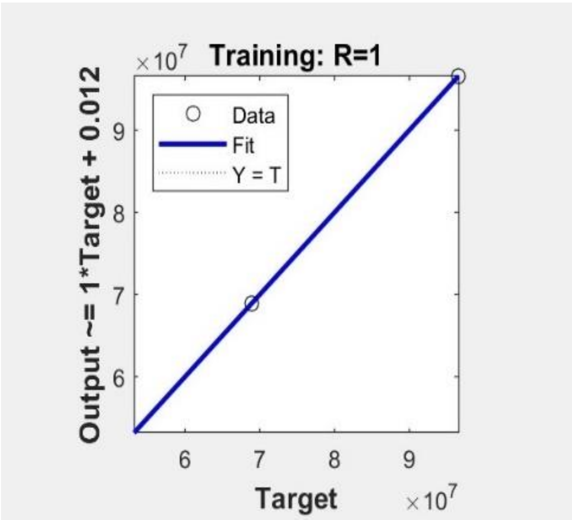

Fig - 2: Quantitative NN Training Regression

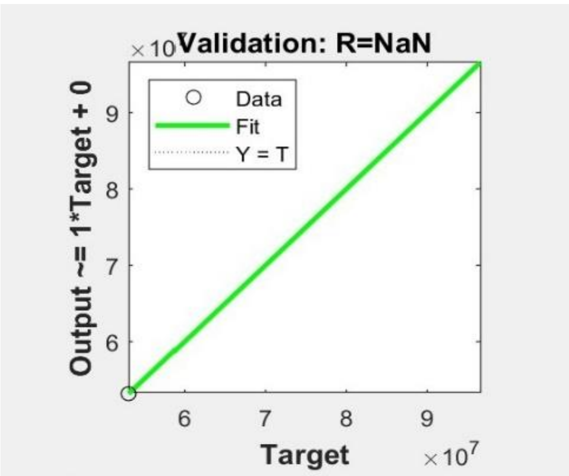

Fig - 3: Quantitative NN Validation Regression

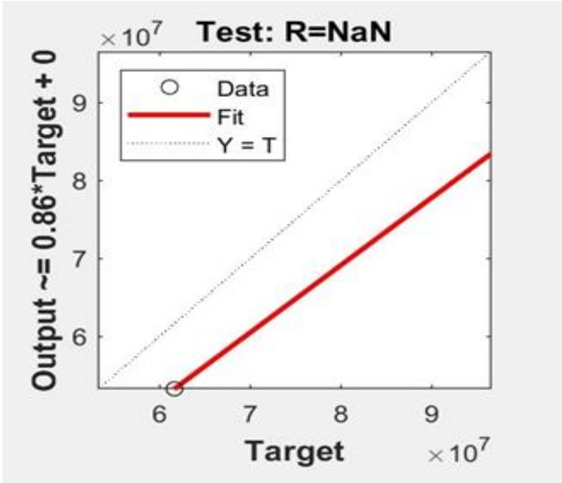

Fig - 4: Quantitative NN Test Regression

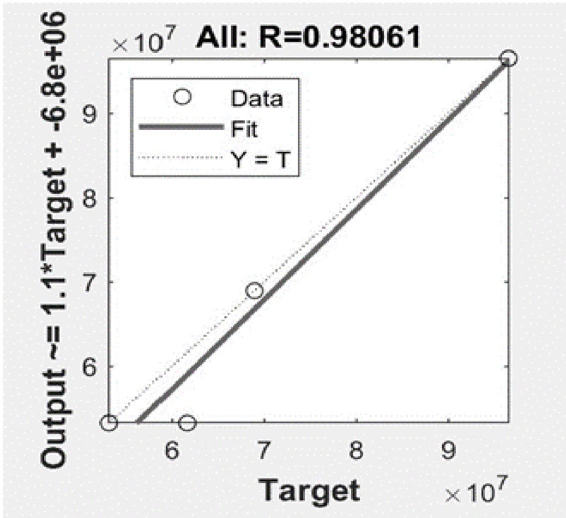

Fig -5: Quantitative NN Total Regression

5. CONCLUSIONS

The research study demonstrated that the Neural Network exhibited absolute error rates of 13.6 %, 0, 2×10^{-6} %, and 10^{-9} % when compared to actual costs in different projects. Prior research has found that the maximum absolute inaccuracy is 1.73 %, while the average absolute percentage error is 0.44 %. This indicates that the accuracy of the ANNs created for the sample of construction projects costs is relatively high and deemed acceptable. The authors urge for the creation of a larger artificial neural network.

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