Univerzitet u Beogradu
Poljoprivredni fakultet
Institut za poljoprivrednu tehniku
Naučni časopis
POLJOPRIVREDNA TEHNIKA
Godina XLIX
Broj 4, 2024.
Strane: 39 – 53

University of Belgrade
Faculty of Agriculture
Institute of Agricultural Engineering
Scientific Journal
AGRICULTURAL ENGINEERING
Year XLIX
No. 4, 2024.
pp. 39 – 53

Original Scientific paper
Originalni naučni rad
DOI: 10.5937/PoljTeh2404039U

ANALYSIS OF COST CONTROL CHALLENGES IN THE CONSTRUCTION INDUSTRY, USING ARTIFICIAL NEURAL NETWORK

Jesam Abam Ujong[1], Okechukwu Oduma[2*], Michael Elvis Mbadike[3]

[1]*Department of Electrical/Electronics and Computer Engineering, Veritas University, Bwari, Abuja, Nigeria*
[2]*Department of Agricultural and Bioresources Engineering, Michael Okpara University of Agriculture, Umudike, Abia State, Nigeria*
[3]*Department of Civil Engineering, Michael Okpara University of Agriculture, Umudike, Abia State, Nigeria*

Abstract: The construction industry frequently encounters significant cost control challenges that can impact project efficiency and profitability. Addressing these issues requires advanced predictive models that can accurately forecast construction cost and identify influential factors. This research aims to leverage on Artificial Neural Network (ANN) model to predict and evaluate construction cost challenges using loss function parameters, comparing its performance with that of multiple linear regression (MLR). A comprehensive dataset of 199 responses from a questionnaire and survey result were derived from various construction projects.
The multiple linear regression (MLR) result yielded an R value of 0.669757, R^2 value of 0.448574 and an adjusted R^2 value of 0.43, indicating limited explanatory power or a weak predictive capability and indicating that the model does not account for much of the variability.

These results underscore the limitations of MLR in handling complex, non-linear relationship within the data. In contrast, an ANN architecture of 7-35-1 was implemented and analyzed in MATLAB, using a Feed-Forward Back propagation with a training function of Levenberg-Marquardt. Conversely, the ANN model demonstrated superior performance, with training, testing, and validation R values of 0.993, 0.99221, and 0.98499, respectively, and an overall R^2 value of 0.99216.

*Corresponding Author. E-mail: odumaoke@gmail.com
ORCID: 0000-0002-5165-2397

The training state of the ANN showed the best gradient of 7.0860 at epoch 2, while the validation performance peaked at 124932260 at epoch 5. The loss function parameters, root mean squared error (RMSE) of 0.81 was obtained. These findings suggest that ANN provided a more accurate and reliable approach for predicting construction cost challenges compared to MLR, highlighting the potential of advanced machine learning techniques in addressing cost control challenges in the construction industry and as well indicating a robust predictive capability across different subsets of the data.

Keywords: *Construction, Cost, MATLAB, Optimization, Prediction.*

INTRODUCTION

The construction industry plays a pivotal role in the economic development and growth of any country, making it one of the main contributors to the Gross National Product (GNP). This sector encompasses a wide range of activities, including residential, commercial, and industrial building projects, infrastructure development and the maintenance and renovation of existing structures. However, the construction industry is a cornerstone of economic development, driving growth through direct contribution to GNP, employment generation, stimulation of related industries, and infrastructure development. Its broad impact on various aspects of the economy underscores its vital role in fostering national prosperity and improving the standard of living, [1].

Effective cost control is indeed a cornerstone of successful construction project management. It ensures that projects are completed within their allocated budgets, which is crucial for the financial health of construction firms and the satisfaction of clients. This helps ensure that construction projects stay within their allocated budgets, by monitoring and managing costs throughout the project lifecycle, project managers can prevent cost overruns, which can lead to financial loses and damage a contractor's reputation. Cost control in construction project management involves a comprehensive set of strategies, practices, and methodologies aimed at minimizing the risk of cost overruns while optimizing project performance. Successful cost control not only ensures financial stability but also contributes to the timely delivery of high-quality results that meet or exceed stakeholder expectations [2]. Effective cost control is indeed a foundational element of successful construction project management which involves planning, monitoring, and managing all cost associated with a project to ensure that it is completed within the approved budget [3].

Author [4], stated in his studies that construction cost control faces numerous challenges due to the dynamic and complex nature of construction projects. Changes can occur in this project due to unforeseen event or circumstances such as unpredictable site conditions, design changes, material price fluctuations, labor shortages and productivity, regulatory compliance, technological changes, stakeholder's expectations, contractual disputes, weather impact, supply chain disruption, project complexity and financial management. Cost control challenges is a factor of concern; thus, this requires proactive planning, robust risk management, real-time monitoring, and flexibility to adapt to changing conditions. Poor cost performance and cost overruns in construction projects are pervasive issues affecting both developing and developed countries.

These challenges stem from a multitude of complex factors, each contributing to the difficulty of maintaining budgetary control. Inaccurate cost estimation is a major factor, often resulting from reliance on incomplete data or overly optimistic projections. This can lead to significant discrepancies between projected and actual costs. Significant issues also range from frequent design and scope changes during the construction phase, these modifications which may be driven by client requests, regulatory requirement, or unforeseen site conditions, often lead to additional and unplanned expenditures [5]. Supply chain issues are another contributing factor.

Delays in the delivery of materials, equipment failures, and fluctuations in materials prices can disrupt project schedules and budget. Labor issues, including shortages of skilled workers, labor strikes, and low productivity, also add to the financial strain on construction projects. Regulatory and compliance costs can increase unexpectedly when there are changes in laws or new requirement that necessitate additional permits, inspections, or project modifications. Financial mismanagement including poor cash flow planning and the lack of sufficient contingency funds can further worsen cost overruns [6].

Addressing these issues requires a multifaceted approach. Improving cost estimation through the use of advanced tools and techniques can enhance budget accuracy, enhanced project management practices including detailed planning, regular monitoring and effective communication among stakeholders are crucial for maintaining control over cost. Risk management strategies, identifying potential risk early, and developing mitigation plans can help prevent unexpected cost from escalating. However, incorporating contingency funds into project budgets and maintaining flexibility to adapt to changes are essential for managing unforeseen expenses. The adoption of technologies such as Building information modeling (BIM) and project management software can improve coordination, cost tracking, and overall efficiency [7], [8].

Authors [9], conducted a study that revealed a significant issue in construction project budgeting; every project examined experienced cost discrepancies. Their findings indicated that 100% of the projects under study suffered from some form of cost divergence. A deeper analysis of these discrepancies showed 76.33% of the project were underestimated in their initial budget, meaning the actual costs exceeded the projected figures. Conversely, 23.67% of the projects were overestimated, where the initial budget allocations were higher than the actual cost incurred. These findings highlight the pervasive challenge of achieving accurate cost estimation in construction projects, the high incidence of underestimation suggests that many projects encounter unexpected expenses or inefficiencies that were not accounted for during the planning phase. This could be due to a range of factors including unforeseen site conditions, changes in project scope, material price fluctuations, and labor issues.

Overestimation, although less common, also poses problems as it can lead to inefficient allocation of resources and potential financial strain on project stakeholders who may set aside more funds than necessary.

This research is aimed at predicting a model for the challenges of cost control in the construction industry, with the machine learning tool (artificial neural network), the following are the objectives of the study Prediction of ANN model for the cost control challenges using survey questionnaire, Comparative analysis of ANN and MLR and to evaluate the ANN model performance using loss function parameters and multiple linear regression analysis.

This research significance is tailored to improve the cost control process in construction projects, which would lead to more efficient projects, could lead to better understanding of the factors that affects cost control, which could lead to improved cost control practice, to help reduce the financial risk associated with construction projects, and to ensure that projects are completed on time within budget with standardized strategies of cost control.

MATERIALS AND METHODS

This study employs mixed method research incorporating both quantitative and qualitative data to investigate the causes of cost increase in Cross River State. The quantitative data will be gathered through structured questionnaire, while qualitative insights will be derived from open ended questions included in the survey. The data will be analyzed using an artificial neural network (ANN) to identify and predict a cost model.

Study Area

The research is focused on construction project within Calabar Municipal in Cross River State, Nigeria (Figure 1), the area is chosen due to its diverse range of construction activities, which provides a rich dataset for analyzing cost fluctuations and underlying causes. Calabar Municipal is a local government area within Calabar, the capital city of Cross River State, it covers an area of 142km^2. Geographically, it is located between latitude 04^0 15'N, and longitude 08^0 25' E. According to the 2006 census, Calabar Municipal has a population of 179,392, to the north it is bordered by the Kwa River in Odukpani and to the northeast, it is bordered by the Calabar River. The predominant ethnic group in Calabar Municipal, are the Efiks and the Qua people. These groups have rich cultural heritages and play a significant role in the socio- economic activities of the area, the main languages spoken are Efik and Qua, which reflect the dominant ethnic groups.
Calabar Municipal is a hub for various economic activities, including trade, tourism, and construction. However, the city is known for its historical significance and as a center for cultural festivities, such as the annual Calabar Carnival.

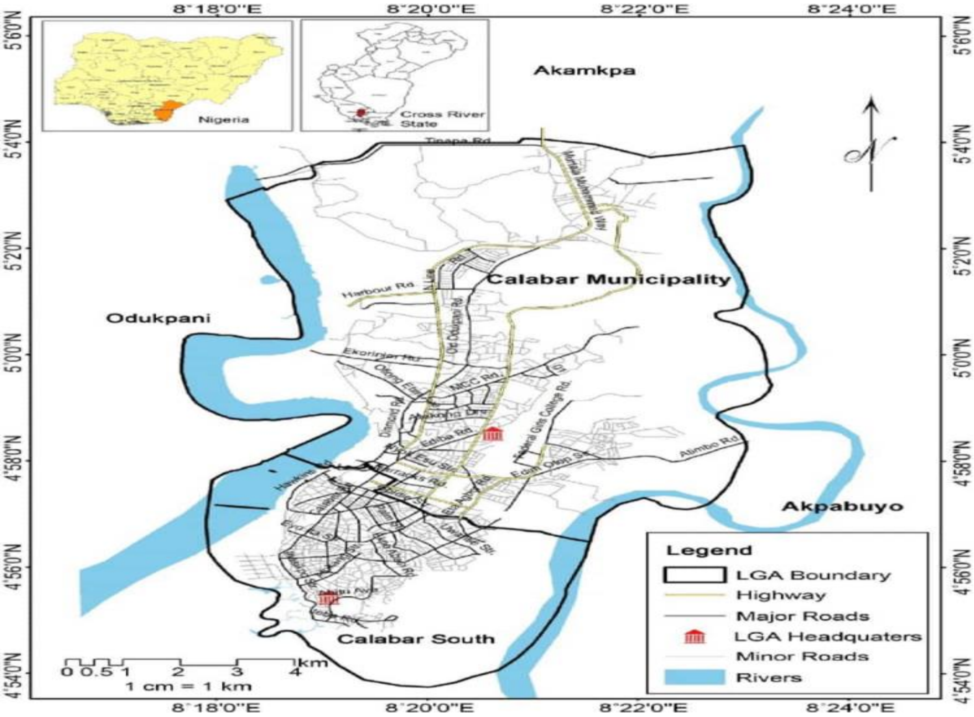


Figure 1. Map of the Study Area (Office of the surveyor general, cross river, [10].

Data Analysis Techniques

The response collected from the questionnaire will be compiled into a structured dataset, data cleaning will be performed to handle missing values, remove duplicate and any inconsistencies. The input variables include, cost control methods, cost estimation accuracy, estimated costs, project duration, economic conditions, resources availability and an output variable of actual cost. The data processing was carried out through normalization where the input variables were scaled to a range suitable for the ANN, typically between 0-5, to ensure efficient training.
However, from fig. 2, an architecture design was done which entails the input layer, hidden layer and output layer.

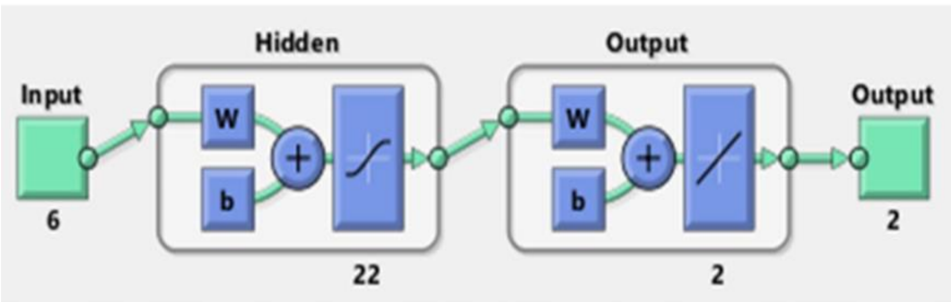


Figure 2. ANN Architecture, [1].

Model Performance Evaluation

The performance of the developed ANN model was evaluated to affirm its ability to estimate or predict the response parameters with an acceptable degree of accuracy. To validate the performance of the ANN model, a multiple linear regression (MLR) model was developed as a benchmark. The performance metrics used for evaluation is Root Mean Squared Error (RMSE). Root mean squared error measures the square root of the average of the squared difference between actual and predicted values. It gives a higher weight to larger errors, making it sensitive to outliners. Mathematically, it is expressed as:

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(E_i - M_i)^2}{n}} \quad \text{……… (1)}$$

Where is:
E_i, the actual value,
M_i , the predicted value,
n, the data point [11], [12].

Experimental Database

The derived data from the questionnaire and survey were systematically sorted and organized to facilitates a comprehensive evaluation of the factors affecting cost control challenges in construction projects within Calabar Municipal.

A total of 199 response was gotten from the questionnaire and survey and was analyzed using MATLAB. The experimental database was structured into multiple tables to organize the data effectively, the main table contained on each construction project including all input and output variables, [1].

RESULTS AND DISCUSSION

Demographical characteristics.

From table 1, the gender distribution of respondent reveals a significant disparity, with males comprising the majority (80%) of the sample and females representing 20%. This gender in balance may reflect the gender demographics within the construction industry in Calabar Municipal.

The age indicates that the majority of respondent 60% fall with the 20-35 years age group, suggesting that younger professionals are heavily represented in the construction sector.

The 36-45 years age group is the second most common, accounting for 31.3% of respondent. This distribution suggests that the industry also has a substantial number of mid-career professionals. The representation of older age group 46-60 years and 60 years is significantly lower, which could be due to retirement or a lower presence of senior professionals actively participating in project management and fieldwork. 71.5%, 4.4%, 7.9%, 3% and of 13.2% of the respondents are civil engineers, builders, contractors, clients, and other team players involved in construction industry respectively. The years of experience of the respondents showed 80.7% for 1-20 years, 14.7% for 21-30 years, 3.6% for 31-45 and 1% for people above 45 years as recorded by, [13].

Table 1. Respondents' Demographical Characteristics

S/N	Variables	Division	Percentage %	Frequency
1.	Sex	Male Female Total	80 20 100	159 40 199
2.	Age	20-35 36-45 46-60 60 > Total	60 31.3 7.3 1.6 100	119 62 15 3 199
3.	Occupation	Civil Engineer Builder Contractor Client Others Total	71.5 4.4 7.9 3 13.2 0 100	142 9 16 6 26 0 199
4.	Years of experience	1-20 21-30 31-45 Others Total	80.7 14.7 3.6 1 100	161 29 7 2 199

Statistical Functions

Table 2 presents the Statistical functions for output and input variables. The standard deviation of Actual cost (Ac), 1.3575 and sample variance of 1.8427 indicates a moderate spread of data points around the mean. These measures reflect the variability in the responses concerning cost control method, the average value of cost control method is 1.8598, suggesting that, on average, respondent rated cost control methods relatively low, with median of 14809 indicates the middle value of the dataset is significantly a skewed distribution, the predicted cost (Pc) shows a large value of the median. The actual duration (Ad) has a standard deviation of 223.93 and a variance of 5.0147 indicating a wide range of actual duration and showing significant variability in the responses. The various mean result gave a central tendency of the dataset, these values can be used as a benchmark for comparing other variables as suggested by [14] and [15].

Table 2. Statistical functions for output and input variables

Parameters	Standard deviation	Sample variance	Median	Mean
Actual Cost	1.3575	1.8427	14809	1.8598
Actual duration	223.93	5.0147	442	499.43
Economic condition	0.7215	0.5206	2	1.6025
Planned cost	9.5951	9.2666	10958	1.5348
Planned duration	214.45	4.599	41880	464.86
Resources availability	0.5345	0.2857	1	1.4503
Construction method	0.523	0.1346	1	1.2206

Multiple Linear Regression (MLR) Result

From table 3.0, with R =0.669757 and R^2 = 0.448574, the model explains only 4.48% 0f the variability in the dependent variable, which is quite low. This suggest that the independent variables in the model are not very effective at explaining the variation in the dependent variable in MLR. The adjusted $R^{2\,=}$ 0.43 is even lower, indicating that when the number of predictors is considered, the model's explanatory power decreases further. This could be due to overfitting.

The standard error of 98269 represent the average distance that the observed values fall from the regression line, providing a measure of model's accuracy as obtained by [16] [17].

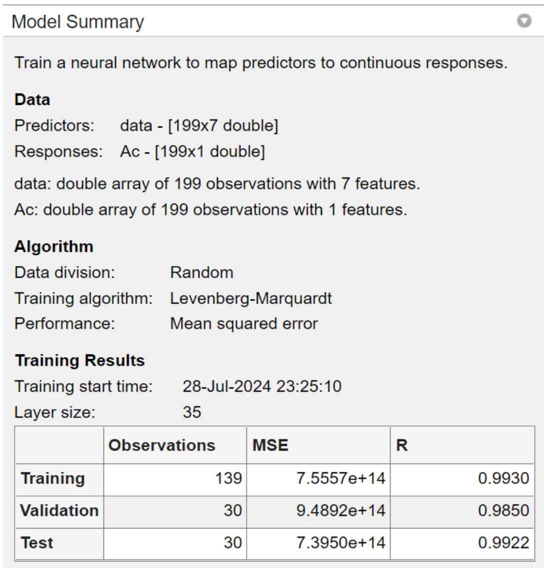
Table 3. Regression Model Summary

Regression Statistics	
Multiple R	0.669757
R Square	0.448574
Adjusted R Square	0.431342
Standard Error	98269009
Observations	199

Artificial Neural Network (ANN) Model Development

From the survey data results, the factors which effects the cost control challenges were sorted as the independent variables which consists of, cost control method, actual duration, planned cost, planned duration, economic conditions, resources availability and Project budget. The model framework is designed as seven-input variables and one-output target response (Actual cost). The processing parameter settings for the neural network model is presented in Fig. 3 which showed a 7-35-1 two-layer feed-forward network with tensig hidden neurons and linear output neurons, can fit multi-dimensional mapping problems arbitrarily well, given consistent data and enough neurons in its hidden layer. In order to determine the best performing n-neurons, mean squared error (MSE) and R-value's evaluation criteria were used in this analytical study.

From the performance test, at 35 number of neurons produced the optimal generalization results in terms the test criteria result with respect to training, validation and testing of the network as shown in figure 3,7. This is in agreement with the observations of [18] and [19].


Model Summary

Train a neural network to map predictors to continuous responses.

Data
Predictors: data - [199x7 double]
Responses: Ac - [199x1 double]

data: double array of 199 observations with 7 features.
Ac: double array of 199 observations with 1 features.

Algorithm
Data division: Random
Training algorithm: Levenberg-Marquardt
Performance: Mean squared error

Training Results
Training start time: 28-Jul-2024 23:25:10
Layer size: 35

	Observations	MSE	R
Training	139	7.5557e+14	0.9930
Validation	30	9.4892e+14	0.9850
Test	30	7.3950e+14	0.9922

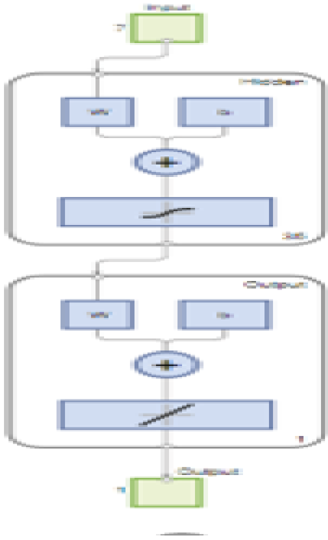


Figure 3. ANN Architecture

Training State of the ANN

The provided training results for ANN model indicate the state of a gradient at 7.0860 in figure 4, with specific observations about the epochs and the onset of overfitting. The gradient value of 7.0860 suggest the magnitude of the gradient during training, if this value is relatively large, it could indicate that the model is learning significantly from the data and has not reached convergence yet. Monitoring gradient values helps in understanding the training dynamics and whether the learning rate needs adjustment. The model performance on the validation set start to degrade at epoch 1, suggesting that the optimal performance on validation data was achieved at this point. After epoch 1.5, the model's ability to generalize to new data begins to decline. From epoch 3 onwards, the model start overfitting. This means that while the model continues to improve on the training data, it performs worse on the validation data. This is in accordance with the findings of [20].

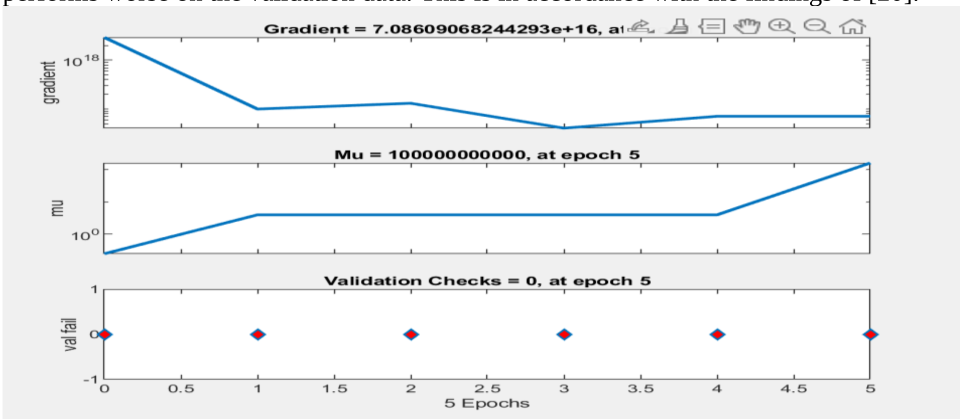


Figure 4. Training State of the ANN

Validation Performance of the ANN

MSE which was the loss function parameter used to evaluate the model performance for validation of the ANN network developed as shown in Fig. 5 presenting the best validation performance of 124932260 at Epoch 2 for the optimized network (7-35-1). The result indicated satisfactory model performance with the smart model capable of predicting the target output parameters accurately generalizing the sets of complex input variables with minimum error as noted by [21].

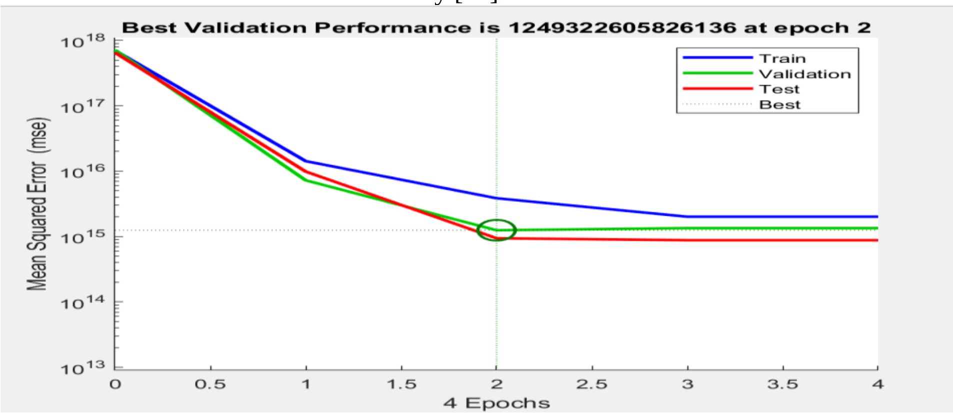


Figure 5. Validation Performance of the ANN

Error Histogram of the ANN

Figure 6 shows how the error histogram is a useful tool for visualizing the distribution of distribution of prediction errors in a model. In this case, you have an error histogram with 20 bins for training, test, and validation data, with an overall error mean of 1.74. The error histogram provides a graphical representation of the difference between predicted and actual values. The errors are divided into 20 bins, allowing us to see how the errors are spread across the data. A mean of 1.74 indicates a slight bias in the model's predictions. This value being close to zero suggest that, on average, the model's predictions are slightly lower than the actual values which agrees with the observations of [22].

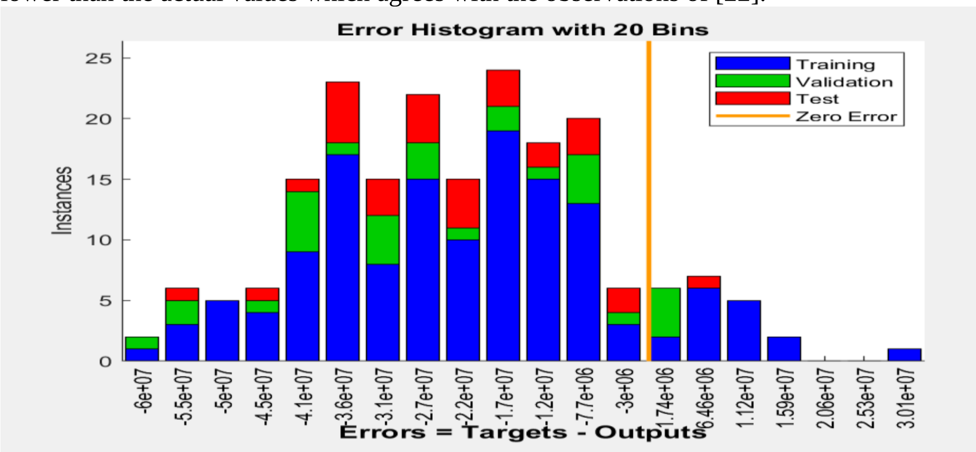


Figure 6. Error Histogram of the ANN

Regression Plot of the ANN

The regression results for the ANN model indicate the performance of the regression on different data subset: training, test, validation and all combined Figure 7). The training R with value of 0.993, this R value represents the correlation between the predicted and actual values on the training data. An R value of 0.993 is relatively high, suggesting that the model fits the training data well and captures most of the underlying patterns. The test R value is slightly lower than the training R value, at 0.99221. this indicates that the model generalizes fairly well to unseen data, although it performs slightly less effectively on the test data compared to the training data. The decrease is minor, suggesting that there is no significant overfitting. However, the validation R value of 0.98499 is close to the training R value, which implies that the model the model maintains its performance on validation data. This is a good indication of model stability and consistency. Finally, the combined R values for all data is 0.99216, which consolidates the performance across the entire dataset. This value being close to the training and validation R values further reinforces that the model has a good overall fit and is reliable. In conclusion the regression results for ANN model are very promising. The high and consistent R values across training, test, and validation sets indicate a well-balanced model with strong predictive capabilities and good generalization to new data. This model can be considered reliable for practical applications where accurate predictions are required. This is in line with the findings of [22] and [23].

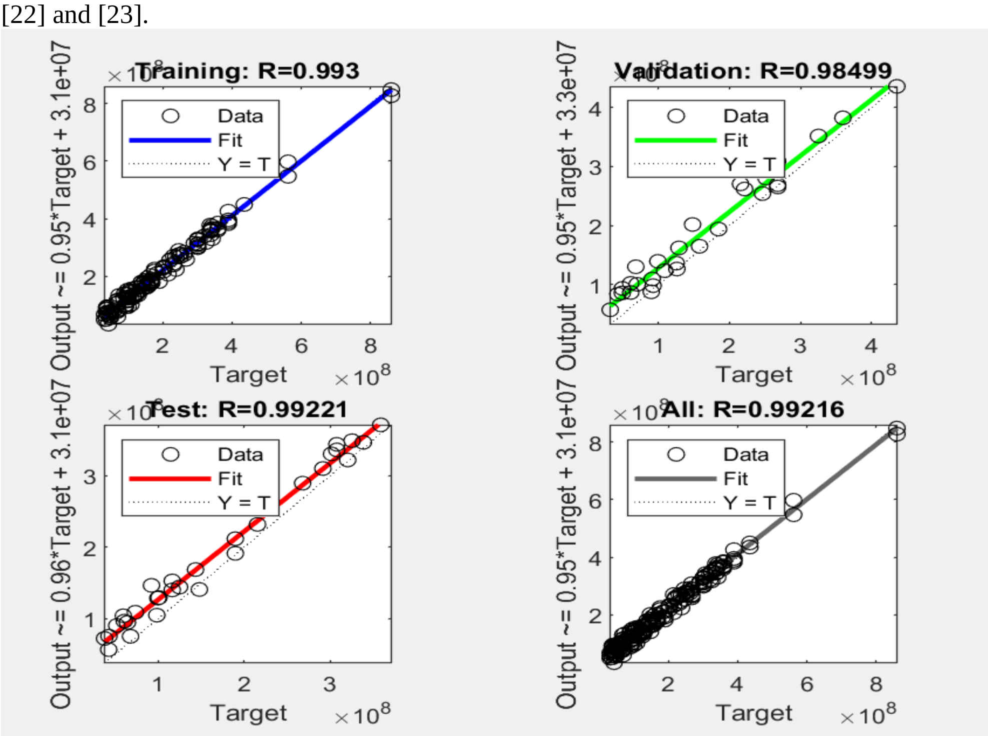


Figure 7. Regression Plot of the ANN

Functions Fit for Output Layers

Figure 8 shows an output function is a function that an optimization function calls at each iteration of its algorithm. Typically, you use an output function to generate graphical output, record the history of the data the algorithm generates, or halt the algorithm based on the data at the current iteration. The function fit shows an error of 6 and inputs of 5.7 while the outputs and target show high training targets and low training outputs.

However, the training outputs falls below 0 to -3 and same results is achieved for the test outputs. This result shows a good performance for the function of fit.

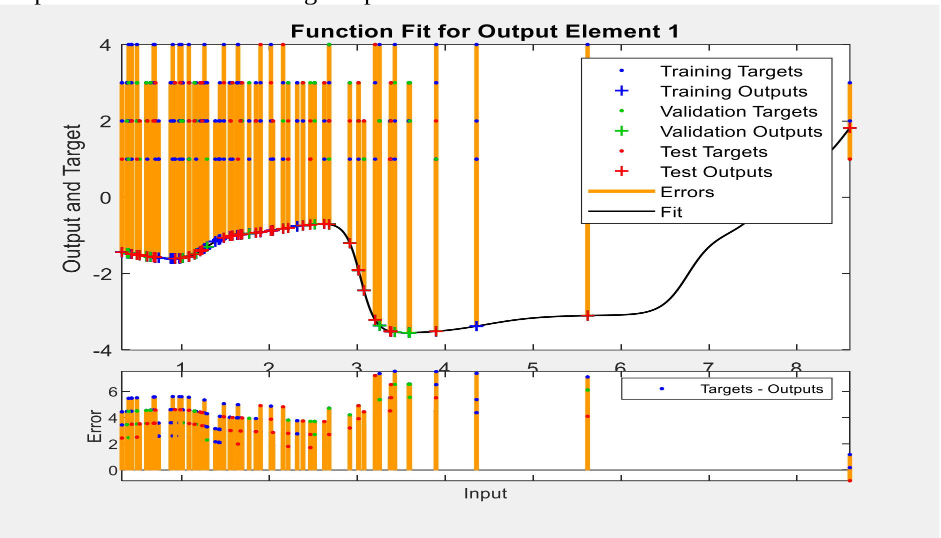


Figure 8. Functions Fit for Output Layers

CONCLUSIONS

This study has demonstrated the significant advantages of employing Artificial Neural Network (ANN) models over traditional multiple linear regression (MLR) in predicting construction cost and addressing cost control challenges within the construction industry. By analyzing a dataset of 199 responses using MATLAB, this dataset was used in comparing the performance of the ANN model with the traditional multiple linear regression (MLR), the ANN's ability to handle complex non-linear relationships within the dataset enables more accurate and reliable cost forecasts. The MLR analysis, with its R value of 0.669757 and R^2 value of 0.448574, revealed its limitations in explaining the variability in construction cost. In contrast, the ANN model, designed with a 7-35-1 architecture, achieved substantially better results, with training, testing, and validation R values indicating robust predictive capabilities. The optimal training state, with a gradient of 7.0860at epoch 9 and a validation performance of 124932260 at epoch 2, further shows the ANN model's effectiveness.

In conclusion, the findings of this study advocate for the integration of machine learning techniques, particularly ANN, in the construction industry's cost control practices.

The superior performance of the ANN model over MLR suggest that adopting such advanced predictive models can lead to more accurate cost forecast, improved resources allocation, and enhanced overall project management. Future research could explore the application of other machine learning algorithms and expand the dataset to further validate these findings and enhance the model's predictive accuracy. By leveraging these innovative techniques, the construction industry can achieve more efficient cost management, ultimately contributing to more successful project outcomes.

RECOMMENDATIONS

i. The construction industry should invest in developing and implementing machine learning techniques, like ANN, to enhance project management and cost control practices

ii. Future research should explore the application of ANN to other construction project management challenges, such as schedule prediction and risk management.

iii. Integrating ANN models with existing project management software can streamline the cost estimation process and provide real-time insights. This integration can facilitate better decision making and allow project managers to respond swiftly to cost variations and project changes

REFERENCES

[1] Jesam, A. U., Mbadike, E. M. and Alaneme, G. U. 2022. Prediction of cost and duration of building construction using artificial neural network. Asian J. Civ. Eng. https://doi.org/10.1007/s42107-022-00474-4.

[2] Elhegazy, A. H. *et al.*2022. Artificial intelligence for developing accurate preliminary cost estimates for composite flooring systems of multi-storey buildings. J. Asian Archit. Build. Eng. 21(1). pp.120–132. https://doi.org/10.1080/13467581.2020.1838288

[3] Kerzner, H.2000. Project Management: A systems approach to planning, scheduling, and controlling, John Wiley, 7th Ed.

[4] Mohd S, Mazianah R, Nurdiana A, Mohd H. 2022. challenges of cost management technique implementation during pre – tender in Klang Valleyconstruction project, https/doi.rg/10.1051/e3sconf/202234705009.

[5] Rajguru, A. and Mahatme P. 2016. Effective techniques in cost optimization of construction projects. Int J Inf Future Res. 3(5):1646–1658. http://ijifr.com/searchjournal.aspx.

[6] Lewis, J.P.2011. Project Planning, Scheduling & Control; a hands-on guide to bringing projects in time and on budget, 5th edition, MacGraw-Hill, New York, USA.

[7] Shanmugapriya S. and Subramanian D. K. 2013. Investigation of significant factors influencing time and cost overruns in Indian construction projects. International Journal of Emerging Technologies, 3(10). pp.734–740.

[8] Sunjka B. P. and Jacob U. 2013. Significant causes and effects of project delays in the Niger delta region Nigeria. SAIIE25 Proceedings: Stellenbosch South Africa. http://citeseerx.ist.psu.edu/viewdoc/download?doi=10.1.1.882.9428&rep=rep1&type=pdf.

[9] Mahamid, I., and Amund, A.2010. Analysis of cost diverge in road construction projects. In: *Proceedings of the 2010 Annual Conference of the Canadian Society for Civil Engineering*, 9–12 June 2010, Winnipeg, Manitoba, Canada.

[11] Ritter, A., and Munoz-Carpena, R. 2013. Performance evaluation of hydrological models: Statistical significance for reducing subjectivity in goodness-of-fit assessments. *Journal of Hydrology, 480*(1). pp.33–45. https:// doi. org/ 10. 1016/j. jhydr ol. 2012. 12. 00.

[12] Alaneme, G.U., Mbadike, E.M., Attah, I.C., and Udousoro, I. M. 2022. Mechanical behaviour optimization of saw dust ash and quarry dust concrete using adaptive neuro-fuzzy inference system. *Innovative Infrastructure Solutions., No7*, p.122. https://doi. org/10. 1007/ s41062-021- 00713-8.
[13] AlSehaimi, A., & Koskela, L. 2008. What Can be Learned from Studies on Delay in Construction ?. Proceedings for the 16th Annual Conference of the International Group for Lean Construction, pp.95–106.
[14] Onyelowe, K. C., Fazal, E. J., Michael, E. O., Ifeanyichukwu, C.O., Alaneme, G.U.,&Chidozie,I. (2021). Artificial intelligence prediction model for swelling potential of soil and quicklime activated rice husk ashblend for sustainable construction. Journal Kejuruteraan., 33(4), pp.845–852.
[15] Rofooei, F.R., Kaveh, A., & Masteri-Farahani, F. 2011. Estimating the vulnerability of concrete moment resisting frame structures using artificial neural networks. International J. of Operational Research, 3(1), pp.433–448.
[16] Okonkwo, U. N., Agunwamba, J. C., & Iro, U.I. 2016. Geometric models for lateritic soil stabilized with cement bagasse ash. Nigerian Journal of Technology, 35(4), pp.769–777.
[17] Okonkwo, U. N., Arinze, E. E., & Ubochi, S.U. 2021. Predictive model for elapsed time between mixing operation and compaction of lateritic soil treated with lime and quarry dust for sub-base of low-cost roads. International Journal Pavement Research Technology. https://doi.org/10.1007/s42947-021-00022-4.
[18] Çelik, S., & Tan, Ö. 2005. Determination of preconsolidation pressure with artificial neural network. Civil Engineering and Environmental Systems, 22, pp. 217–231. https:// doi. org/10. 1080/ 10286 600500383923.
[19] Sobhani, J., Najimi, M., Pourkhorshidi, A. R., & Parhizkar, T. 2010. Prediction of the compressive strength of no-slump concrete: A comparative study of regression, neural network and ANFIS models. Construction of Building Materials, 24, pp.709 –718.
[20] Erzin, Y., Gumaste, S. D., Gupta, A.K., & Singh, D.N. 2009. ANN models for determining hydraulic conductivity of compacted fine grained soils. Canadian Geotechnical Journal, 46, pp. 955–968.
[21] Erzin, Y., Rao, B.H., Patel, A., Gumaste, S.D., Gupta, A.K., & Singh, D. N. 2010. Artificial neural network models for predicting of electrical resistivity of soils from their thermal resistivity. Inter national Journal of Thermal Sciences, 49, pp.118–130.
[22] Shahmansouri, A. A., Akbarzadeh Bengar, H. & Jafari, A. 2020. Modeling the lateral behavior of concrete rocking walls using multi objective neural network. J. Con. Struct. Mater. 5(2), pp.110–128. https://doi.org/10.30478/jcsm.2021.272480.1192.
[23] Ambrule, V. R., & Bhirud, A. N.2017. Use of artificial neural network for pre design cost estimation of building projects. Interational Journal on Recent and Innovation Trends in Computing and Communication, 5(2), pp.173–176.

ANALIZA PROCENE KONTROLE TROŠKOVA U GRAĐEVINSKOJ INDUSTRIJI, KORIŠĆENJEM VEŠTAČKE NEURONSKE MREŽE

Jesam Abam Ujong, Okechukwu Oduma, Michael Elvis Mbadike

[1]*Department of Electrical/Electronics and Computer Engineering,*
Veritas University, Bwari, Abuja, Nigeria
[2]*Department of Agricultural and Bioresources Engineering,*
Michael Okpara University of Agriculture, Umudike, Abia State, Nigeria
[3]*Department of Civil Engineering, Michael Okpara University of Agriculture,*
Umudike, Abia State, Nigeria

Apstrakt. Građevinska industrija se često susreće sa značajnim izazovima procene kontrole troškova koji mogu uticati na efikasnost i profitabilnost projekata. Rešavanje ovih problema zahteva napredne modele predviđanja koji mogu precizno predvideti troškove izgradnje i identifikovati uticajne faktore.

Ovo istraživanje ima za cilj da iskoristi model ANN-Artificial Neural Network , Veštačke Neuronske Mreže-VNM, za predviđanje i procenu predpostavke troškova izgradnje koristeći parametre funkcije gubitka, upoređujući njegove performanse sa performansama MLR -Multiple Linear Regression, (Višestruka Linearna Regresija-VLR).

Sveobuhvatan skup podataka od 199 odgovora iz upitnika i rezultata ankete izveden je iz različitih građevinskih projekata.

Rezultat višestruke linearne regresije (VLR) je dao R vrednost od 0.669757, R^2 vrednost od 0.448574 i prilagođenu vrednost R^2 od 0.43, što ukazuje na ograničenu moć objašnjenja ili slabu prediktivnu sposobnost i ukazuje da model ne uzima u obzir veći deo promenljivih parametara.

Ovi rezultati naglašavaju ograničenja MLR (Multiple Linear Regression) u rukovanju složenim, nelinearnim odnosima unutar podataka. Nasuprot tome, VNM, (ANN), prema arhitekturi 7-35-1 je implementirana i analizirana u programu MATLAB, korišćenjem širenja povratnog protoka sa funkcijom Levenberg-Markuardt.

Nasuprot tome, model ANN je pokazao superiorne performanse, sa R vrednostima obuke, testiranja i validacije od 0.993, 0.99221 i 0.98499, respektivno, i ukupnom vrednošću R^2 od 0.99216. Stanje -VNM, (eng. ANN-Artificial Neural Network) je pokazalo najbolji gradijent od 7.0860 u epohi 2, dok je performansa validacije dostigla vrhunac na 124932260 u epohi 5. Dobijeni su parametri funkcije gubitka, prosečna kvadratna greška (RMSE-Root Mean Square Error) od 0,81.

Istraživanja i rezultati sugerišu da je VNM, (eng. ANN- Artificial Neural Network) pokazuje tačniji i pouzdaniji pristup za predviđanje procene troškova izgradnje u poređenju sa MLR (Multiple Linear Regression), ističući potencijal naprednih tehnika mašinskog učenja u rešavanju procene kontrole troškova u građevinskoj industriji i takođe ukazujući na snažnu sposobnost predviđanja u različitim podskupovima podataka.

Ključne reči: *Konstrukcija, cena, MATLAB, optimizacija, predviđanje.*

Prijavljen:
***Submitted*: 22.09.2024.**
Ispravljen:
***Revised*: 21.10.2024.**
Prihvaćen:
***Accepted*: 02.12.2024.**