Research Article *Open Access*

Journal of Scientific Engineering Advances

ISSN: 3071-0723

DOI: doi.org/10.63721/25JSEA0108

Artificial Neural Network for Green Building Cost Prediction

Comfort Olubunmi Ade-Ojo[1*], Deji Rufus Ogunsemi[2], Oluwaseyi Alabi Awodele[3] and Charles Egbu[4]

[1]*Department of Quantity Surveying, Federal University of Technology, Akure, Ondo State, Nigeria*
[2]*Department of Quantity Surveying, Federal University of Technology, Akure, Ondo State, Nigeria*
[3]*Department of Quantity Surveying, Federal University of Technology, Akure, Ondo State, Nigeria*
[4]*Leeds Trinity University, England, UK*

Citation: Comfort Olubunmi Ade-Ojo, Deji Rufus Ogunsemi, Oluwaseyi Alabi Awodele Charles Egbu (2025) Artificial Neural Network For Green Building Cost Prediction. J. of Sci Eng Advances 1(3) 1-12. WMJ/JSEA-108

Abstract

The increased cost of production is one of the challenges to green building development. The purpose of this study was to develop a cost-predictive model to enhance decision-making for green building development among stakeholders in South-Western Nigeria. Tertiary Education Trust Fund (TETFund) projects executed from 2011 to 2018 constitute the study population. Secondary data, on design parameters and elemental cost details, were collected for the cost-predictive model using the Artificial Neural Network (ANN). The results showed that the ANN model predicts the cost of a green building project with 99% accuracy. The study concludes that the Artificial Neural Network model is a veritable tool to effectively manage the cost of the TETFund green building project's development with up to 99% accuracy. The study recommends the ANN model for cost prediction in making an informed decision for green building development. The institutions should use the ANN model to forecast proposed green building costs. ANN is useful for benchmarking approvals by the TETFund for green TEIs.

***Corresponding author:** Comfort Olubunmi Ade-Ojo, Department of Quantity Surveying, Federal University of Technology, Akure, Ondo State, Nigeria.

Submitted: 10.10.2025 **Accepted:** 26.10.2025 **Published:** 03.11.2025

Keywords: Cost, Green Building, Prediction, Artificial Neural Network

Introduction

Globally, the construction of green buildings is hampered by the presumption that they are more expensive than conventional structures. The availability of an appropriate cost prediction tool at the early stage of the design process can improve the construction of green buildings. This is because the client's decision to build or not is influenced by the expected initial capital outlay [1,2]. A chance to predict the cost of the anticipated project could help Nigeria and other countries expand their green construction industries.

Cost prediction is the process of determining the likely cost of a proposed project before the intended client begins the project. It is most beneficial at the start of the building project when a significant portion of the design decisions are made. Therefore, the ability to estimate the cost of green building development using cost prediction models may impact the adoption of green building practices and procedures positively. The cost of building projects can be estimated using a variety of forecasting models and methods [3-8]. However, these models were not for green building cost prediction. Earlier research on the cost of green building development established the difference between conventional building and green building costs explored the cost and benefits of sustainable construction [9-11]. However, few empirical studies exist with outcomes or findings to help would-be developers determine the likely cost of green building projects right from inception. Hence, this study explores the use of ANN as a predictive model for estimating the cost of green educational institutional buildings in South-Western Nigeria, educational facilities can be either public or private.

Materials and Methods

Green Building Cost

Costs for green buildings typically vary in direct proportion to the client's demands. One of the obstacles to the adoption and implementation of green building practices is the perception that green buildings are more expensive. However, this belief is gradually fading as cost information on green buildings becomes more widely known and accessible [4,10,12,13-15]. The literature on the price of constructing green demonstrates that the marginal cost of building green is not as assumed according to [9,10,15]. The diversity in green building costs depends on various sizes and design complexities just like the conventional buildings. However, advised determining the cost of sustainable building designs using cost prediction models before making any financial decisions [9].

Cost Prediction

Construction projects are unique; no two building projects will ever be the same in terms of design, location, workmanship, environment, site condition, labor, or even the economics under which they are carried out. Cost projections can be made at various phases of the building project. The unit approach, the square meter method (Cost/m2), approximate amounts, elemental cost planning, cubic meter, and the storey enclosure method are a few techniques for preparing a cost estimate. Each of these approaches has its strengths and applications. The square meter method—also known as the cost/m2 g.f.a. is more widely used due to its simplicity of use and the fact that the majority of published cost data is in this format. The degree to which the predicted cost closely approximates the actual construction cost is referred to as accuracy. This denotes the likelihood that the cost will be the same as the estimate while prediction is the capacity of the estimated cost to represent the real cost. According to [16,17], traditional estimating methodologies are criticized for their high rate of failure in estimating the actual cost. With the introduction of computer-aided estimating methods, it is possible to create cost estimates that are quite precise. These are referred to as parametric cost estimate techniques-based cost models. The parametric estimation method uses cost-relevant parameters (such as floor area, cubic volume, electricity generating capacity, steel production capacity, etc.) to determine a cost function in the conceptual estimate for new projects [18].

Cost Estimation for Green Building Development

Cost is one of the fundamental factors used to evaluate a project's success. Time, quality, and user satisfaction are a few more. For a project to succeed, it must be possible to estimate costs with a reasonable degree of certainty during the design phase. The high level of uncertainty associated with construction projects has been shown in research to make traditional estimating methods ineffective. In light of this, it is essential to adopt contemporary cost modeling techniques [16-19,20]. Because developers prioritize upfront costs while green building development is more of a lifelong endeavor (what will happen in the future), it has been difficult to estimate the cost implications of green building development. The purpose of cost estimating at the conceptual stage of the project is to establish the target cost consequently, giving a guiding tool for the designer in consideration of the client's budget. The integrative design process necessary for green building development functions on this assumption.

Cost Predictive Models

Predictive models are used directly to estimate a response (output) given a specific set of characteristics (input) or indirectly to influence the decision-making process. Getting the data can take up to 80% of the time needed to create the model, making it one of the most frequently disregarded problems with predictive modeling. There are various algorithms for predictive modeling, including decision trees, time series analysis, and logistic regression. According to, the choice of the prediction model is based on its speed, accuracy, familiarity, convenience of use, and availability of data [8,16-21]. The accuracy of the cost estimate (prediction) depends on the volume and quality of data available and the technique used [22]. Research has demonstrated that the NN can replicate the human brain through learning. With its record-breaking high performance, the NN offers a practical instrument for estimating the cost of green buildings from the very beginning of conceptual design. This is just one benefit the ANN has over other cost modeling methods. A NN is a predictive model that examines huge amounts of labeled data independently for correlations between different data points. It can detect even miniature relationships that only become apparent after analyzing millions of data points. Today's Artificial Intelligence (AI), including Image Recognition, Smart Assistants, and Natural Language Generation (NLG), are all based on neural networks. This application has significantly improved cost estimating compared to regression methods. It can handle non-linear issues and carry out tasks utilizing incomplete data sets, insufficient information, and extremely difficult problems by replicating the learning function of the human brain [23]. Due to its high level of accuracy in comparison to other predictive models and its use in construction cost estimation, this is frequently referred to as an Artificial Neural Network (ANN). The difficulty of having little data at the design stage for the creation of green buildings makes the ANN more suitable for model development. This is a result of its capacity to simulate and learn information while identifying subtle patterns and producing predictions, or the output [24].

Artificial Neural Network (ANN) Model

The ANN architecture follows a network representing the relationship between variables and their connection [20-25,26]. The ANN technique was also used by to create a model for the cost premium of 74 certified green buildings in the USA [5]. The study by Tatari and Kucukvar is the only one that specifically addresses the development of green buildings out of the several applications of ANN to cost prediction models. Research has also shown that the ANN is better suited for cost prediction models hence, the ANN was applied for this study. also created an ANN model to predict the cost of hypothetical building projects in the Gaza Strip [23]. The ANN employed nine building functional element categories to classify costs: the area of the ground, the number of storeys, the stairs and lifts, the external walls, the number of windows, the external doors, the floor height, the internal doors, the slabs, and the number and length of the columns in between. The neural network model was created using a total of 169 projects. The model had a Mean Absolute Percentage Error (MAPE) of 10% within the acceptable range of accuracy for ANN models.

Methods

The population covers 47 TETFund projects completed in the Federal Universities and Polytechnics in South-Western Nigeria from 2011 to 2018 under the Federal government policy on public procurement [27]. These were academic buildings such as classrooms, computer laboratories, libraries, and faculty office buildings. Since the population was manageable, the study adopted a census survey. Only 16 of the TEIBs achieved the minimum 40 points of the LEED v4 project checklist for New Construction and Major Renovation. The 16 buildings constituted the purposive sample used for the predictive model.

The individual assessment was carried out on the TEIBs in the study area to determine the LEED score. According to the LEED v4 rating system, green buildings are categorized based on the level of certification required or attained. Secondary data of the 16 projects were collected using a proforma. Building construction details such as the type of building, age, total cost (per m^2g.f. a), and size of the project were available for only 12 out of the 16 projects. Others included the elemental cost breakdown of the projects per m^2gfa using the contract Bill of Quantities (BOQ) and architectural drawings to indicate the design parameters of the building.

The choice of variables was based on the building design variables at the conceptual stage. The conceptual design stage is the most critical for decision making according to [17]. All other building elements depend on these variables. The choice of the building elements (quantity and quality) resultantly determines the greenness of the building and consequently the elemental cost. Hence, data on the design variables, such as Gross Floor Area, Storey Height, Number of Floors, and Site Area, were collated for developing the prediction model. This influences the elemental impact, energy, and life cycle cost-related impacts. At the same time, it affects the thermal performance of the building envelope, daylighting and shading, natural ventilation, renewable energy systems, and water resources. All these are important for green building development [28].

Data Analysis

The elemental cost data (per m^2gfa) of the various buildings, with LEED score of 40 and above, were used viz; Substructure, Superstructure, Internal finishes, Fittings, Services, and External works. The cost data were used as training cases for the Artificial Neural Network (ANN). The process involved in the development of ANN includes Data collection, data processing, building a network, training network, and testing the network. These processes are discussed as follows;

Data Collection

The minimum number of points for certification using the LEED scoring system is 40 [29]. Hence, the data for twelve (12) TEIBs with Gb-CI of 40 was collected for the development of the cost model using the ANN. Although the ANN performs better with a large amount of data, its ability to learn makes it suitable for cost prediction with not too large data samples. It, therefore, has the advantage to be able to perform tasks with incomplete data sets usually associated with the design stage of building projects [24-30]. The data collated for the projects included elemental cost numbering (6), giving 72 data samples from 12 minimum certified projects for the model development. At the early design stage (Conceptual design) where 70% of the decision for green building happens, the little information available is about the building shape, area of construction, and building height which directly impacts the building volume [17]. The elemental cost breakdown per m^2 gross floor area (Gb-C/m^2g.f.a.) is calculated for the individual building project. This is used as the weight in the regression equation. Therefore, the green building cost is predicted per square meter gross floor area of the intended green building project.

Data Processing

The model consists of six input variables including factors that will influence the impact of the building construction on the physical environment. The input variables are Storey height (m), Gross floor area (m2) Gross floor Area, Number of Floors (Nr), Site Area (m2), Building Volume (m3), and Building Foot Print (m2). These are the independent variables as shown in Table 1. The cost (GB-cost/m^2gfa) which is a sum of the elemental costs of External work, Services, Fittings and Furnishings, Internal finishing, Superstructure, and Substructure is the dependent variable for the ANN model (Table 2).

Data is generally normalized for confidentiality and effective training of the model where the input data must be normalized between an upper and lower bound [26]. The different methods to scale the data include the z-normalization, min-max scale, etc. The min-max method was used to scale the data in the interval [0, 1] because scaling in the intervals [0, 1] tends to give better results. This is recognized to improve the performance of trained networks [24].

Building the Network k

Although there are various training algorithms, the NN models are usually trained with standard Backpropagation with Stochastic Gradient descent (SGD). However, with the need to speed up convergence by increasing the training speed, several algorithms have been developed, one of which is Resilient propagation (Rprop) [31]. The ANN model was developed using the Rprop for the Learning algorithm. The Rprop was introduced as a learning algorithm for the training of Neural Networks by Riedmiller and Braun[32]. The Rprop performs direct weight adjustment in multi-layer feed-forward networks for backpropagation.

Backpropagation is an algorithm widely used for supervised learning using the SGD. Although similar to regular backpropagation, it has two main advantages over regular backpropagation. First, it trains the network faster than the back-propagation method. Second, the backpropagation uses the SGD to train the network.

Table 1: Independent Variables

S/N	Gross Floor Area (m2)	Number of Floors (nr)	Storey Height (m)	Site area (m2)	Building Volume (m3)	Building footprint (m3)
1	2,400	2	9	1,800	21,600	1,348
2	3,616	3	14	1,685	50,624	1,637
3	3,219	2	12	2,136	38,628	2,026
4	2,999	2	11	1,597	32,989	1,500
5	913	1	9	1,940	8,217	1,800
6	12,500	2	9	7,280	1,12,500	7,020
7	2,146	1	8	3,200	17,168	2,845
8	1,807	1	8	5,645	14,456	5,465
9	5,134	2	9	2,673	47,826	2,567
10	1,147	1	5	1,790	5,735	1,650
11	2,908	2	10	1,981	29,080	1,454
12	7,200	3	11	3,000	79,200	2,600

As the depth and complexity of an artificial neural network increases, the gradient propagated backward by the standard SGD becomes increasingly smaller known as the "vanishing gradients" problem. It leads to negligible weight updates, thus, slowing down the training process considerably (Chen & Su, 2010). This challenge is resolved with Rprop. According to, the Rprop trains four times faster than backpropagation [31]. Using Rprop does not require the specification of any values as opposed to the backpropagation for the learning rate and the momentum factor [31-33].

Data was assigned to the training and test sets using random sampling. The R programming language (R code), was used in preparing the ANN. Eighty percent of the dataset was used for training and 20% for model testing. A training set finds the relationship between dependent and independent variables while the test set assesses the model performance.

Table 2: Dependent Variables (N'000)

S/N	Substructure	Super Structure	Internal Finishes	Fitting and Furnishings	Services	External Work	Total Cost
1	8,153.75	80,977.04	7,699.22	1,112.50	10,205.84	2,642.21	1,10,790.56
2	14,532.25	49,406.31	21,582.15	4,162.33	8,218.58	7,273.86	1,05,175.48
3	13,428.02	49,806.91	25,301.50	1,988.87	13,772.53	2,358.93	1,06,656.76
4	3,474.06	41,264.34	12,137.93	4,162.33	6,526.03	293.41	67,858.10
5	12,347.26	19,561.00	10,996.76	4,162.33	10,483.94	2,358.93	59,910.22
6	924	14,052.00	7,705.00	1,600.00	112	214	24,607.30
7	10,841.00	37,768.28	10,139.00	6,769.00	12,355.00	2,962.00	80,834.28
8	4,259.77	53,288.36	22,251.76	4,162.33	7,240.99	265.64	91,468.85
9	16,283.34	12,209.93	14,253.00	12,865.85	7,191.54	4,704.17	67,507.83
10	10,490.00	15,406.70	9,720.30	4,162.33	12,504.53	2,358.93	54,642.79
11	31,310.82	47,438.88	14,996.36	637.76	15,775.73	515.82	1,10,675.37
12	8,958.25	32,039.66	14,253.00	4,162.33	21,945.32	2,358.93	83,717.48

Waziri (2010) reported that output with a 10% mean standard error is considered acceptable for the ANN model, while Elbeltagi (2017) discussing the level of accuracy of different types of estimate noted that the expected percentage error for conceptual cost estimate is ± 10-20 %. Since there are no specific means to establish the network configuration, trial and error were used to determine the architecture with minimal error (Heaton, 2018). Three, out of the developed, configurations were compared for best performance. The NN performance is assessed based on five factors: coefficient of correlation (r), coefficient of determination (R2), the value of the standard error of estimates, (Sy,x), and the Mean square error (MSE), and the mean absolute percentage error (MAPE). The MAPE shows the percentage level of accuracy. Thus, the network configuration with the least MAPE was chosen in developing the model.

The network configuration that has the best fit with minimum MAPE with a high R^2 value is 6:5:1 for the ANN. The number of epochs used for the ANN Architecture was 263 at which point the network shows convergence with a 0.005554 error rate. The network architecture for the ANN, therefore, consisted of an input layer with six input variables (elements), hidden layer(s) of five neurons, and an output layer with one output; the predicted cost of the green development (Cost/m^2gfa). The network architecture for the DNN was 6:10:8:6.

The hyperbolic tangent activation function was used for the neurons in both the hidden and the output neurons. The hyperbolic tangent activation function had a better output compared with Networks trained with the Sigmoid Logistic function. Hence, each neuron's output was calculated while the output of the output neuron was calculated using equations iii and iv respectively.

$$f(x_j) = \tan h \sum_{i=1}^{n} (x_i w_{ij} + \theta_{ij}) \qquad \text{............................ } i$$

$$f(x_k) = \frac{1}{1+e \sum_{j=1}^{n} x_j w_{jk} + \theta_{jk}} \qquad \text{.......................... } ii$$

where Xi is the input variable value, w_{ij} is the connection weight between the input neuron i and hidden neuron j. WJ,k is the connection weight between the hidden neuron j and output neuron k. $\theta i,j$ and $\theta j,k$ is the bias terms for the respective neurons, and i, j, and k are the number of neurons for the input, hidden, and output layers, respectively. Once the network is built, the ANN model is trained by exemplars that include an individual set of input/ output data.

As ANN models are processing elements and connections with adjustable strengths, it learns by adjusting the connection weights between neurons iteratively. The Rprop algorithm does not require supervised learning since the learning rates use a fixed update value δij. This is increased or decreased multiplicatively at each iteration by an asymmetric factor η+ and η− respectively, depending on whether the gradient concerning wij has changed sign between two iterations or not [30]. The mean square error between the target output and the model output was minimized overall the training data by adjusting the connection weights within the model using the equation:

$$MSE = \frac{\Sigma(y_i - \hat{y}_i)}{n} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots iii$$

Given;

$$\text{Gb-C/m}^2 = \sum_{i=1}^{n} Q \sum_{j=1}^{n} X \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots iv$$

Where Gb-C = Green building cost, Q = design variable quantity, $\sum_{j=6}^{n} X$ = sum of elemental cost and i = the particular design variable while j = the particular elemental cost.

Gb-C/m² is the dependent variable,
Q and X = the independent variables (constraints)
Q Storey height (sh, m), Gross floor area (gf, m²), Number of Floors (nf, Nr), Site Area (sa, m²), Building Volume (bv, m³), Building Foot Print (bf, m²).
i = the treatment that is subject to variation (design variable)
J_1; substructure, J_2; superstructure, J_3; internal finishes, J_4; fittings, J_5; services and J_6; external works.

$$\text{Gb-C/m}^2 = \sum_{i=1}^{n} (Q_{sh} \sum_{j=1}^{n} X + Q_{gf} \sum_{j=1}^{n} X + Q_{nf} \sum_{j=1}^{n} X + Q_{sa} \sum_{j=1}^{n} X + Q_{bv} \sum_{j=1}^{n} X + Q_{bf} \sum_{j=1}^{n} X) \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots vi$$

The Artificial Neural Network model is validated with the test dataset. After the training process, test data was used for validation and generalization of the trained network. If the network can generalize the output for this testing data, it means that the neural network can predict the cost correctly for new data. Hence, the network is validated [23]. The findings were benchmarked with the traditional statistical approach using the Linear Regression model. After obtaining the prediction results of the ANN model for both training and testing data, the results were compared with the regression model for validation. Multiple regression analysis conducted on the training data set of the neural network model test the effect of input variables on the dependent variable, Gb-Cost. Multiple regressions generate a linear equation that best describes the relationship between several independent variables and a dependent scale variable.

Results

The Artificial Neural Network (ANN) model used 80% of the dataset for training. Six neurons used in the input layer include Gross Floor Area, Number of Floor, Storey Height, Site Area, Building Volume, and Building

Foot Print while Gb-cost/m2g.f.a. was the output neuron with five hidden neurons. The assignment of the data to the training and test set was randomly done. Trial and error were used to reduce the error by varying the number of neurons in the hidden layer and the number of epochs. The minimum error achieved with five hidden neurons and 263 number epochs is 0.005554 using the Resilient-backpropagation (Rprop) method. The graphical representation of the ANN model with the weights on each connection (Figure 1).

Table 3: The different configurations for the ANN model

Model	Architecture	Error	Epoch
m1	06:04:01	0.002207	416
m2	06:05:01	0.005554	263
m3	06:09:01	0.000903	93

Table 4: Data for Three different ANN configurations

Model		Training	Testing		Training	Testing
m1	**r**	0.9997	0.99	**R^2**	0.9994	0.99
m2	**r**	0.9943	0.9876	**R^2**	0.9887	0.9753
m3	**r**	0.999	0.9034	**R^2**	0.9979	0.8161
m1	**Sy,x**	828.071	30627.2	**MSE**	533323	312675190
m2	**Sy,x**	3433.24	11691.4	**MSE**	9167768	45563234
m3	**Sy,x**	1384.23	26175.1	**MSE**	1490288	228378651
m1	**MAPE**	0.6867	20.5497			
m2	**MAPE**	2.4885	6.6654			
m3	**MAPE**	1.1357	11.3865			

Table 4 shows the prediction power of the developed neural network model. The correlation coefficient, r, was 0.9943 for training data, the corresponding coefficient of determination, R2, was 0.9887. The coefficient of determination is much higher than 0.7, a generally accepted R2 value [5]. It shows that the prediction rate is significantly high for the developed ANN model. The neural network model for the testing data set is also good with a correlation coefficient, r, as 0.9876 and the corresponding coefficient of determination, R2, as 0.9753. Again, the coefficient of determination shows that the prediction rate is significantly high for testing data. Although the data set was relatively small, the figures showed a very close approximation between the actual green certified project values/m2g.f.a. and the neural network output. The mean percentage error of the prediction model (MAPE) is 6.6654 meaning ±7% approximately.

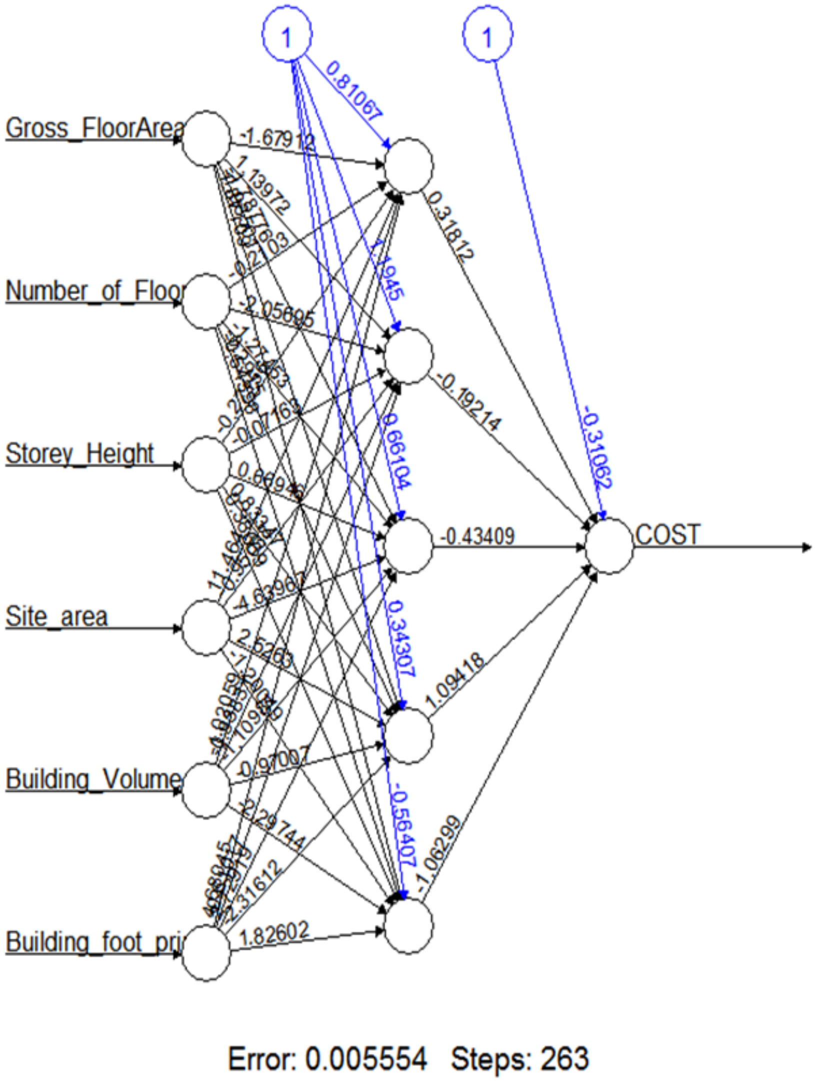

Figure 1: Artificial Neural Network to predict the Gb cost/m2g.f.a.

Table 5: ANN result for the Training and Testing Datasets

Comparison Factor	ANN Training	ANN Testing
r	0.9943	0.9876
R2	0.9887	0.9753
Sy,x	3433.2391	11691.4372
MSE	9167768.448	45563234.48
RMSE	3027.8323	6750.0544
MAPE	2.4885	6.6654

Discussion

The results of the model's development demonstrate that the ANN is capable of making cost predictions for green building development at a rate greater than the industry norm of 0.7. For both the training set and the testing set, the ANN model's coefficient of determination is 0.9943. This demonstrates that the ANN model has excellent performance in estimating the expenses of green buildings. This supports earlier statements that the ANN outperformed other predictive models when used to estimate costs for various building construction features. The model outperforms earlier models for cost premium prediction of green buildings, with R2 values for training and testing of 0.9835 and 0.9617, respectively [5].

Despite the ANN's success in forecasting development costs for green buildings, its application to cost prediction in Nigeria has not been thoroughly investigated. The small size of the data set is caused by the institutions' lack of green building development practises and their low compliance with adopting green building principles. As a result, the TEIs that offer quantity surveying courses must teach their students how to use ANNs to estimate costs. Additionally, it has enormous promise as a real cost forecast tool for the country's quantity surveyors, particularly for the construction of green buildings. The difficulties of early cost evaluation for green TEIBs are reduced by the TEIs' use of the ANN.

The goal of the study was to create a model to help stakeholders in Nigeria make better decisions on the development of green buildings. With an R2 value of 0.9980, the created ANN model can forecast the price of green construction with 99% accuracy. The study suggests using ANN to estimate the cost of green building projects. This will help intending stakeholders make wise choices when putting into practise green building regulations.

The authors report there are no competing interests to declare.

References

1. Seah E (2009) Sustainable Construction and The Impact on the Quantity Surveyor. 13th Pacific Association of Quantity Surveyors Congress 36-48.
2. Yusuf G A, Mohamed S F, Yusof Z M, Misnan M S (2013) Role of building services quantity surveyors in managing cost of green buildings. Advanced Materials Research 13: 71-74.
3. Adogbo K J, Chindo P G (2009) Promoting sustainable construction industry activities https://www.unido.org/publications/ot/9657330/pdf
4. Bashir A, Suresh S, Proverbs D G, Gameson R (2010) Barriers towards the sustainable implementation of lean construction in the United Kingdom construction organizations. Arcom Doctoral Workshop 1-8.
5. Tatari O, Kucukvar M (2011) Cost premium prediction of certi fi ed green buildings : A neural network approach. Building and Environment 46: 1081-1086.
6. Hussin J Md, Rahman I Abdul, Memon, A Hameed (2013) The way forward in sustainable construction: Issues and challenges. International Journal of Advances in Applied Sciences 2: 15-24.
7. Oke A Emmanuel, Aghimien, D Omoregie, Olatunji, S Olusola (2015) Implementation of value management as an economic sustainability tool for building construction in Nigeria. International Journal of Managing Value and Supply Chains (IJMVSC) 6: 55-64.
8. Alshamrani O S (2016) Construction cost prediction model for conventional and sustainable college buildings in North America Othman. Journal of Taibah University for Science 1-9.
9. Langdon D (2004) Examining the Cost of Green.
10. Langdon D (2007) Cost of Green Revisited: Reexamining the Feasibility and Cost Impact of Sustainable Design in the Light of Increased Market Adoption. https://doi.org/10.1093/jhmas/jrr055
11. Dobson W D, Sourani A, Sertyesilisik B, Tunstall A (2013). Sustainable construction: analysis of its costs and benefits. American Journal of Civil Engineering and Architecture 1: 32-38.
12. Kats G, Capital E, Alevantis L, Berman A, Mills E et al. (2003) The costs and financial benefits of green buildings. In A Report to California's Sustainable Building Task Force https://icma.org/documents/costs-and-financial-benefits-green-buildings.
13. Issa M H, Rankin J H, Christian A J (2010) Canadian practitioners' perception of research work investigating the cost premiums, long-term costs and health and productivity benefits of green buildings. Building and Environment, 45: 1698-1711.
14. Qian Q K, Chan E H W, Khalid A G (2015) Challenges in delivering green building projects:

Unearthing the transaction costs (TCs). Sustainability (Switzerland) 7: 3615-3636.

15. Dalibi S G, Feng J C, Shuangqin L, Sadiq A, Bello B S, et al. (2017) Hindrances to Green Building Developments in Nigeria's Built Environment: "The Project Professionals'Perspectives". IOP Conference Series: Earth and Environmental Science 1-9.
16. Kats G H (2003) Green Building Costs and Financial Benefits. https://icma.org/documents/costs-and-financial-benefits-green-buildings.
17. Lowe D J, Emsley M W, Harding A (2006) Predicting construction cost using multiple regression techniques. ASCE Journal of Construction Engineering and Management 132: 750758.
18. Bragança L, Vieira S M, Andrade J B (2014) Early-Stage Design Decisions: The Way to Achieve Sustainable Buildings at Lower Costs. The Scientific World Journal 1-8.
19. Wang W, Bilozerov T, Dzeng R, Hsiao F, Wang K (2017) Conceptual cost estimations using neuro-fuzzy and multi-factor evaluation methods for building projects. Journal of Civil Engineering and Management 23: 1-14.
20. Challal A, Tkiouat M (2012)The Design of Cost Estimating Model of Construction Project: Application and Simulation 15-26.
21. Waziri S B (2010) An artificial neural network model for predicting construction costs of institutional building projects in Nigeria. In S. Laryea, R. Leiringer, & W. Hughes (Eds.), West Africa Built Environment Research (WABER) Conference of Construction Management and Engineering 63-72.
22. Sonmez R (2005) Review of Conceptual Cost Modelling Techniques. AACE International Transactions EST 07: 1-3.
23. Adegbile B O (2013) Assessment and adaptation of an appropriate green building rating system for Nigeria. Journal of Environment and Earth Science 3: 1-11.
24. Pal Mhashilkar A, Pandey A, Nagphase B, Chandanshive V (2018) Cost Estimation Model (CEM) of buildings by ANN (Artificial Neural Networks) – A Review. International Advanced Research Journal in Science, Engineering and Technology 5: 2393-2395.
25. El-sawalhi N I, Shehatto O (2014) A neural network model for building construction projects cost estimating. Journal of Construction Engineering and Project Management 4: 9-16.
26. Odeyinka H, Lowe J (2002a).A Construction Cost Flow Risk Assessment Model. In D. Greenwood (Ed.), Proceedings of the 18 th Annual ARCOM Conference 3-12.
27. Günaydın H M, Doğan S Z (2004) A neural network approach for early cost estimation of structural systems of buildings. International Journal of Project Management 22: 595-602
28. Tertiary Education Trust Fund (2011). Pub. L. No. 65, A253
29. Saleh M S, Alalouch C (2015) Towards sustainable construction in Oman: Challenges & Opportunities 118:177-184.
30. U.S. Green Building Council. (2013). LEED v4 User Guide.
31. Muqeem S, Khamidi M F, Idrus A B, Zakaria, S Bin (2011) Prediction Modeling of Construction Labor Production Rates using Artificial Neural Network. In Na (Ed.), 2nd International Conference on Environmental Science and Technology IPCBEE IACSIT Press, Singapore Prediction 6: 2-36.
32. Mosca A, Magoulas G D (2015) Adapting Resilient Propagation for Deep Learning. UK Workshop on Computational Intelligence 1-4.
33. Riedmiller M, Braun H (1993) A direct adaptive method for faster backpropagation learning: The rprop algorithm. IEEE International Conference on Neural Networks 586-591.
34. Prasad N, Singh R, Lal S P (2013) Comparison of Back Propagation and Resilient Propagation Algorithm for Spam Classification. 2013 Fifth International Conference on Computational Intelligence, Modelling and Simulation 29-34.
35. Elbeltagi E (2017) Cost Estimating. In Construction Cost Estimating 88-117.
36. Hussin J Md, Rahman, I. Abdul, Memon, A Hameed (2013) The way forward in sustainable construction: Issues and challenges. International Journal of Advances in Applied Sciences 2: 15-24.
37. Hwang B, Zhu L, Wang Y, Cheong X (2017) Green Building Construction Projects in Singapore: Cost Premiums and Cost Performance. Project Management Journal, 48: 67-80.
38. Qian Q K, Chan E H W, Khalid A G (2015) Challenges in delivering green building projects: Unearthing the transaction costs (TCs). Sustainability

(Switzerland)7: 3615-3636.

39. Sonmez R (2005) Review of Conceptual Cost Modelling Techniques. AACE International Transactions, EST 07: 1-3.