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NEURAL NETWORK AND PROBABILTY BASED COST EXPECTATION LIMIT MODEL FOR RESIDENTIAL BUILDING COST

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The aim of this study is to develop a Cost Expectancy Limit Model that could assist clients in having proactive information about construction cost expectation of a particular building type with a view of assisting the client in proactive determination of expected construction cost of a building under predetermined conditions. Two population frames were used in this context. First, a population frame of 1500 samples of actual construction cost of residential building in Lagos state Nigeria out of which 1000 samples of As-built cost (Actual cost) of residential buildings were used, in artificial neural network data training and model development using MATLAB Neuro tools. The second population sample was 250 samples of construction professionals, out of which 200 samples was picked for purpose of questionnaire administration to capture data on factors that could influence building cost expectancy. Mean Item Score, Simple Percentage, and Relative Agreement Index of SPSS package was used to analyze and process the data. Cost expectancy limit was developed with parameters trained with Artificial Neural Networks, while factors that influence the accurateness of the expectancy model were articulated, such as economic factors, political factors, activity of maestros, macro and micro economic variables, and corruption factors, among others. The study recommends the use of the model and strategy for effectiveness in accurate prediction of construction cost among other things.

Keywords: Parameters, Prediction, Neuro tools, Agreement, Information.

1 COST IN BUILDING

Contributions Cost is one of the major challenges faced during each phase of construction. Many construction projects are started and later cannot be completed because of many reasons, including financial challenges. This is because clients do not have proper information concerning the project and do not know how to plan financially for the project, leading to project abandonment and other challenges like time and cost overrun, which causes a waste of resources, and it becomes a nuisance to the environment, especially when it keeps reoccurring (Efi and Andrea 2011). Cost forecasting if done poorly also contributes highly to this; it will lead to estimates being lower than the actual value and improper funding of the project. This requires cost expectancy limit to be developed by reliable means, as there are many approaches to developing this. The causes of project abandonment are numerous, and most of them are directly or indirectly related to cost. The professionals in the industry of construction have great concerns about the costs, i.e., the actual cost which is the final cost, the estimated cost or the initial cost at the beginning of the project and the tender figure. Professionals are concerned in particular with the wide gap that exists between these costs (Boussabaine 2010, Offei–Nyako *et al.* 2016).

2 RESEARCH METHODOLOGY

Relative Agreement Index (R.A.I.) is a metric that is usually used for carrying out of rating scale evaluation and derives an index that can serve as a ratio of measurement of opinion of the respondents. An agreement scale of 1 to 5 was used: Strongly, Agree, Agree, Strongly Disagree, Disagree, and Neutral. In this section, population sample, sample size, and methods of analysis were presented. Also, the method of analysis to be used for the analysis of the various parameters that could help in the development of cost expectancy limit which could lessen or eliminated cost related challenges on site that sometimes lead to project abandonment, was presented using the relative agreement index (R.A.I.) The R.A.I. method was used to derive the results manual where SA=5, A=4, N=3, D=2, SD=1 (Jafarzadeh *et al.* 2013). The population constituents for the purpose of this research work was categorized along the line of clients which include the type of buildings which can be residential in nature, religious, academic, office, health facilities and special buildings. The population frame for this study includes private buildings that were used for residential purpose. The projects are those completed within the last 5 years. The initial cost and as-built cost extracted from the project documents of these projects were used as modeling parameters for the neural network-based model. Two samples were used in this study. One of these were samples for identifying parameters that influences project abandonment on account of cost related problems and information of importance of cost limit determination in project execution. The second sample was the sample of cost data of completed project used in model development with the aid of neural network data training. In the context of this study, a population frame of 250 was used, of which 200 samples were used for analysis through questionnaires distributed for response collation on parameters that influence project abandonment and importance of development of cost expectancy limit in building. However, for the purpose of training the data with Neural Networks, large samples are needed for modeling. To this end, sample frame of 1500 was used, while a sample of 1000 of actual cost of residential building was used for data training.

Table 1 indicates the parameters that influence project abandonment. "Funds mismanagement" was ranked 1st with a R.A.I. of 0.874 after which "poor construction planning" was ranked 2nd with a R.A.I. of 0.854 and "land or legal disputes" was ranked third with R.A.I. of 0.850. "Improper planning and design and inception of project" is ranked 4th with R.A.I. of 0.844 with "improper project estimates" ranking 5th with R.A.I. of 0.836. Also, "economic recession" ranked 6th with R.A.I. of 0.830, "death of client" ranked 7th with a R.A.I. of 0.814. Closely following is "lack of adequate fund allocation and payment delay" which ranked 8th with R.A.I. of 0.808. "Inflation and bankruptcy of contractor" also ranked 8th with R.A.I. of 0.808 as well. Ranking 10th was "lack of proper assessment" with a R.A.I. of 0.788; following this is "delay in payment" ranking 11th with R.A.I. of 0.780 and ranking 12th is the "project manager incompetence" with R.A.I. of 0.752. Table 2 indicates the importance of developing cost expectancy limit as "prevention of project abandonment" was ranked 1st with a R.A.I. of 0.862 after which "to enable the client determine if the project can continue" was ranked 2nd with a R.A.I. of 0.838 and "keep expenditure within cost limit" was ranked third with R.A.I. of 0.832 (Elfaki *et al.* 2014).

Table 1. Parameters that influence project abandonment.

S/N	Project Abandonment Parameters	Mean	R.A.I	Ranking
1	Fund mismanagement	4.37	0.874	1
2	Poor construction planning	4.27	0.854	2
3	Land or legal disputes	4.25	0.850	3
4	Improper planning and design and inception of project	4.22	0.844	4
5	Improper project estimates	4.18	0.836	5
6	Economic recession	4.15	0.830	6
7	Death of client	4.07	0.814	7
8	Lack of adequate fund allocation and payment delay	4.04	0.808	8
9	Inflation and bankruptcy of contractor	4.04	0.808	8
10	Lack of proper assessment	3.94	0.788	10
11	Delay in payment	3.90	0.780	11
12	Project manager incompetence	3.76	0.752	12
13	Lack of project risk assessment	3.75	0.750	13
14	Change of priority	3.70	0.740	14
15	Inability to adhere to specifications and building codes	3.67	0.734	15
16	Poor quality control by regulatory bodies	3.45	0.690	16
17	Poorly developed clients brief	3.43	0.686	17
18	Negligence of quantity surveyor resulting in wrong estimation	3.37	0.674	18
19	Lack of available skilled personnel	3.33	0.666	19
20	Weakened market conditions	3.28	0.656	20

R.A.I--- Relative Agreement Index

Table 2. Importance of development of cost expectancy limit in building.

S/N	Importance of development of cost expectancy limit	Mean	R.A.I	Ranking
1	Prevention of project abandonment	4.31	0.862	1
2	To enable the client determine if the project should proceed	4.19	0.838	2
3	Keeps expenditure within cost limit	4.16	0.832	3
4	To ensure adequate funding for project delivery	4.15	0.830	4
5	To enable the contractor exercise effective control over resources	4.06	0.812	5
6	Gives rise to effective cost plan	4.04	0.808	6
7	Awareness of financial expectation	4.01	0.802	7
8	Improved building quality and performance	4.00	0.800	8
9	Used as cost prediction	4.00	0.800	8
10	Clients satisfaction with better value for money	3.96	0.792	10
11	Determine overall feasibility of the project	3.91	0.782	11
12	Helps to manage cash flow	3.90	0.780	12
13	Prevention of cost overruns and time overruns	3.90	0.780	12
14	Help target cost to be distributed in a balanced way over the different parts of the building	3.84	0.768	14
15	Enables designers arrive at practical and balanced designs	3.78	0.756	15
16	Allows client to secure a business plan	3.72	0.744	16
17	Promotes effective communication among project team	3.67	0.734	17
18	Help contractor determine if they will bid	3.57	0.714	18
19	To enable the contractor maximize his profitability	3.51	0.702	19
20	Helps to determine source of funds	3.15	0.630	20

R.A.I--- Relative Agreement Index

2.1 Neural Network Training of Sampled Cost Data for Model Training

As a result of the training, the graph in Figure 1 was obtained and the values at the bottom left end. The blue dot graph denotes the true values and the yellow dot on the graph denotes the predicted values. The red line joining them denotes the errors between them. On the bottom left end, the following result was given from the training of the network architecture which is the table above; RMSE= 3.3117e+06; -Square= 0.00; MSE= 1.0967e+13; MAE= 2.7536e+06; The prediction time= ~60obs/sec; The training time=12.494seconds. (Jafarzadeh *et al.* 2013). After the training of the network, a single value was predicted from the trained network by using a coding formula: yfit= trainedmodel.predict. Fcn (X) where X represents the values that were used in the training. A single value was gotten from this prediction, which is 3,050200 naira. Some of the above contains some basic assumptions in application of neural network application.

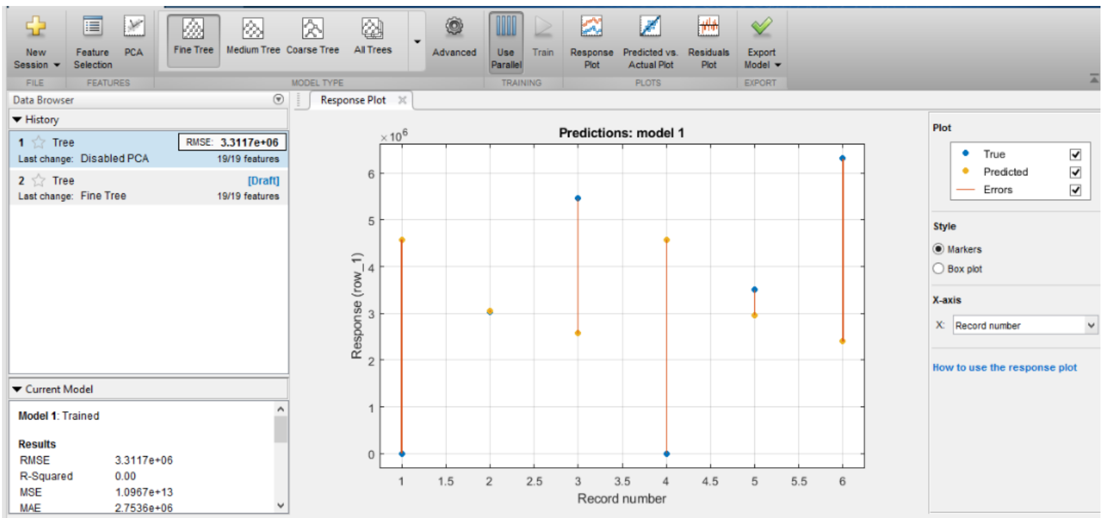

Figure 1. Neural network cost data training pane 1. Source: Mat-lab R2017b (2018)

2.2 Developing Cost Expectancy Limit to Prevent Cost Related Challenges on Site

2.2.1 *Probability estimating*

The PERT (Program Evaluation and Review Technique) was used for the probability estimation technique. The value predicted by the neural network was used to get the range of values that were used in the PERT technique. The nearest cost from the original costs was selected and the optimistic cost, pessimistic cost, and most-likely cost were selected from the nearest cost to the predicted cost.

From Table 1, 2- and 3-Bedroom Bungalows were used as type of building that could be easily built and that can be planned towards. From Table 3, the most likely construction cost for 1-Bedroom bungalow is N4,567,820[$12,723]; 2-Bedroom bungalow is N9,588,000 [$26,707] while 3-Bedroom bungalow project is N13,235,612[$36,868]. For the 1-Bedroom bungalow, the predicted cost was N3,050,200 naira within a close range to the B.O.Q. value. The cost was used as the optimistic cost and the resultant as-built cost as the pessimistic cost. The same trend emerged in the cases of 3-Bedroom Bungalow and 2-Bedroom Bungalow. The expected cost was calculated using the formula in Eq. (1) and the value derived was close to the most-likely cost (Efi and Andrea 2011, Amusan 2012, Buratti *et al.* 2014, Amusan *et al.* 2018b). The Hedonic cost equation used for probability estimation of most-likely cost generated is shown in Eq. (1):

$$ECR= [OP[0.1667]+0.667MC+0.1667PES] \quad (1)$$

where OP=Optimistic Cost; MC= Most Likely Cost and PES is Pessimistic Cost.

Table 3. Table of probability estimating calculation of expected cost limit.

Building Types	Optimistic cost [BOQ Value]	Most likely cost	Pessimistic cost	Expected cost [(0+4M+P)0. 1667]	Expected cost Region
1-Bedroom Bungalow	3,050,55 [$8,497]	4,500,000 [$12,535]	6,356,370 [$17,705]	**4,567,820** [$12,723]	4,500,000 [$12,535]
2-Bedroom Bungalow	9,674,000 [$2,6947]	9,450,000 [$38,441]	10,654,000 [$29,676]	**9,588,000** [$26,707]	9,450,000 [$26,323]
3-Bedroom Bungalow	13,543,670 [$37,726]	13,800,000 [$38,441]	10,670,000 [$29,721]	**13,235,612** [$36,868]	13,800,000 [$38,441]

2.2.2 *Probability cost hedonic model for different probability cost expectations*

The break down of different cost expectation of most-likely cost, pessimistic cost and optimistic cost is presented alongside the Hedonic model in the next sections.

2.2.3 *Probability regression cost hedonic model for expected cost and most-likely cost*

Using Eq. 2(a-d), expected cost and most-likely cost were both calculated:

$$y = mx + c \quad (2a)$$

$$\mathbf{4500000} = 3050550 \text{ x } 0.1576 + 4019233. \quad (2b)$$

$$y = 4500000 – \textbf{Most Likely Cost} \quad (2c)$$

$$m = 3050550 – \text{Optimistic Cost ---}x = 0.1576 – \text{Inflation Rate } c = 4019233 \quad (2d)$$

2.2.4 *Probability cost hedonic model for optimistic cost*

Using Eq. 3(a, b), optimistic cost was calculated:

$$y = mx + c \quad (3a)$$

$$3050550 = 6356370.02 \text{ x } 0.1576 + 2048786.08 \quad (3b)$$

2.2.5 *Probability cost hedonic model for pessimistic cost*

Using Eq. 4(a-c), pessimistic cost was calculated:

$$y = mx + c \quad (4a)$$

$$6356370.02 = 3050550 \text{ x } 0.1576 + 5875603.34 \quad (4b)$$

$$y = 6356370.02 – \textbf{Pessimistic Cost} \quad (4c)$$

These equations represent various hedonic models generated for the purpose of determining the cost dichotomies such as optimistic cost, most likely cost, and expected cost for all categories of different residential building projects.

3 CONCLUSIONS

Factors that influence building cost and building cost expectancy have been reviewed in order to know the factors that affect the cost of building so measures can be taken in order to avoid them or reduce them. The most influential factor was chosen by the respondents and the order of importance was stated in detail in the tables presented in the text. Finally, Probability estimating model that could be used in determining cost dichotomy of projects for purpose of planning was developed which cut across cost determination that covers Most likely, Pessimistic and Most likely cost (Kim *et al.* 2004, Efi and Andrea 2011, Afolabi *et al.* 2018, Amusan *et al.* 2018a, Amusan *et al.* 2018b). The study has generated an hedonic form of a regression model that could capture the Pessinmistic cost optimistic cost and most likely cost of a building type. The hedonic model is described using Eq. (1) as given earlier in Section 2.2.1.

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