Building Cost-Informatics: Neuro-Regression Modeling of Residential Building Project's Cost

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Abstract: Building cost informatics is a body of knowledge that involves application of computer, digital system, building information modeling and state of art software in solving cost issues in building works and presentations in this study adopted building cost-informatics system in developing a model. The aim of the study is to generate a cost prediction model for residential building using a combination of parametric regression method and neural network (an expert system).The main objective of the work is to generate a stable cost prediction algorithm and model from neural network and regression method. Neural network is a conventional method currently being used in cost modeling, given its advantage over traditional regression method the objective is to use the strength of the two methods to generate an hybrid model that could be used in holistic cost prediction of residential building works. To achieve this, One hundred (100) samples of residential building projects were selected at random and divided into two; one part is used in developing network algorithm while the second part is used for model validation. Neural network is used to generate an optimized cost prediction algorithm which was divided into modules: the data optimization module, criteria selection with initializing and terminating modules. The generated algorithm and model was validated with Regression analysis was carried out and Jackknife re-sampling technique. It was discovered from colinearity analysis that there was high level of tolerance and -0.0756 lowest variation prediction quotients to 0.8678 highest variation quotients. Also the Regression coefficient (R-square) value for determining the model fitness is 0.069 with standard error of 0.045. These results attests to the fitness of the model generated. Implication of the above data is that the model algorithm is a stable one which could be processed further into software, it is flexible and adaptive in accommodating new data and variables, thus, it allows for continuous updating.

***Keywords*:** Expert System, Model, Colinearity, Informatics, Residential Building.

Introduction

The provision of shelter is one of the millennium development goals of the United Nations. This is anchored on construction industry and has invariably made construction industry one of the sectors considered as vital in a nation's economic development. It is responsible for employment provision for active group of nation's economy (Skitmore 1990). The contributory ratio of construction sector has however risen in recent time, with more jobs provision on account of high demand for housing. This trend is believed to be instigated on account of global economic meltdown, which has resulted in more demand for space usable for residential facilities. In the mandate of United Nations development programme (UNDP) to developing nations, housing for all by year 2020 is a priority, this has constrained stake holders to channel efforts into evolving speedy approach to housing delivery. This development has resulted in space conversion in to residential accommodation in order to meet ever increasing demand for residential units. However, in order to match delivery speed with demand, factors such as efficiency of building, cost delivery system, time-cost quality target among others need to be taken into consideration (Li, Shen and Love 2005). Cost of the building must be established properly before construction begins, this is considered a critical parameter in measuring the efficiency of building project delivery; therefore, efforts geared toward creating a framework for its proper measurement will be worthwhile (Ogunsemi and Jagboro). In modeling, the framework is as important as the model itself. Series of modeling framework had been adopted in the past, some of them includes: hedonic model, regression model and expert system. Expert system (Artificial Neural Network) are patterned after the natural biological neurons which has ability to map input to output and deduct a meaningful inference, it has the capability of studying data trend even if the series is inconsistent, once the pattern is mastered the network can generalize the trend to predict a consistent series having mastered a previous trend. It is against this background that the study carried out an exploratory approach to cost modeling of office buildings in Nigeria using an expert -based system (ANN).

1.1.1 Objectives of the Study

The objectives of the study include:

i. To generate a stable cost prediction algorithm and model using neural network and regression analysis approach.

ii. To develop a framework or flow chart for model that could be used in residential building construction cost prediction.

1.2 Cost Modeling: Historical Perspective

Building cost model can be defined as the symbolic representation of a building system expressing the content of the system in terms of cost influencing parameters. Cube method was the first model to be used (Skitmore 1990) and was invented 200 years ago.

Floor area method was developed in 1920, while storey enclosure method was developed in 1954. Storey enclosure method was found to be more accurate in cost estimating than cube and floor area methods(Skitmore 1990). However, around mid 1970, Statistical cost modeling technique was evolved; this includes the use of approximate quantity and optimized models. However, during this era, research efforts were concentrated in the direction of validating the applicability of developed model given the seemingly applicable nature of models generated. The developed models are called hedonic model, Rosen (1974) which laid the foundation for the application of model in hedonic form and application of regression-based models.

Regression models are found to be limited in application as a result of their non-flexible nature and margin of error between input and output. Later there was a paradigm shift in the direction of application of expert system as advocated by Brandon (1987). Since then expert have been using expert system good attributes such as capacity to accommodate large data input, consistent output, output and input mapping, consistent output, low variation error between input and output in model generation as has been demonstrated.

1.3 Cost Models In Use

There are two different schools of thought in cost modeling; the product-based and process based. A school of thought classified model as product-based while other classified it as process-based. Product-based model was defined by Moore, Lees and Fortunes (1999) and Ferry (1999) as system that models finished product. Process-based model on the other hand refers to model that is named through the process used to produce it.

However, Mawdesley (1997) and Asworth (1994) presented approaches in modeling as elemental, regression, heuristics and expert system. Modelers had been using regression model since early 18th century, and this system relies on historical cost and has as its shortcoming reliance on historical cost of projects, inability to capture intervening variables that impact project such as price change, and inflation change among others (Moore et al., 1999).

Similarly, Li et al., (2005) was of the opinion that area method of estimating item costs is deficient in the aspect of being influenced by factors other than floor area, Heuristic on the other hand, which has its roots in Monte Carlo simulation, is also deficient because of overdependence on comprehensive study of systems antecedents.

However, expert –based system has been found to have strength in the areas of deficiency of regression models. David and Seer, (2004); Dissanayaka and Kumaraswamy (2007), and Moore et al., (1999) stated that, it generate less error between input and expected output, also, it tends to have variation error the ranging from of 2% to 4% while parametric model(regression model) often have variation error greater than 7%.

1.4 Review of Related Works on Non-Traditional Models [Neural Networks]

There has been a number of studies carried out on the modeling of building cost variables with the aid of Artificial neural networks. Some of the selected articles in this paper covers highway cost modeling, actual construction cost modeling, cost and risk estimating among others. McKim (2005) worked on risk identification using neural network, the study predicted the percentage change in the estimated cost from final cost as the index of risk measurement. Similarly, Gwang-Hee, Sang-Hoon and Kyung-Ink (2004) carried out analysis of different methods of estimating model in use at early stage of construction works, such as regression analysis and neural network, the study concluded that neural network performed best in term of prediction accuracy. Also, Setyawati, Sahirman and Creese (2002) developed a neural network based cost estimating model and used combination of regression and neural network model to generate a regression-based model. In the same vein, Tharwornnwong and Enke (2004) deployed neural network in stock market return forecasting, that study found out that neural network can be used when an accurate results and higher trading results are desirable. It is on this premise that this study used neural network in model formulation.

However, the uniqueness of a typical building project lies in the ergonomic interrelationship among project cost centres. Cost centre refer to project elements commonly found, in an ordered form on a typical project's bill of quantity and bill of estimate. The cost often represents an optimal cost implication of individual elements derived through weighing different cost alternatives through a process referred to as cost adjudication.

Furthermore, a cost decision can be the type that favors forward or backward factoring of cost implication on project cost centres, such as those taken at bid stage of building projects, whereby the cost implications is loaded on elements scheduled to be executed towards the end of the project and at the end of project respectively. Also, since the beginning of the century, there has been a paradigm shift in the direction of research into the art of using classical approach to curtail the negative effect of cost and payment delay on project through use of models. Review of past efforts on models developed to take decision on cost issues in construction work is presented in this section.

Some of the models include bid-balancing models, hedonic models, regression model among others. Bid balancing according to Cattel, Bowen and Kaka (2007) and Christodoulou (2008), is the process by which intelligent approach is used in even distribution of overall project actual cost and profits among project activities without jeopardizing the total bid price for the work. Cattel, Bowen and Kaka (2008) carried out a study on application of bi-unbalancing method for lowering contractors' financial risk and came up with a model. Bill of quantity of completed building projects was used in that study; cost centers of the projects on bill of quantity were classified into two groups and used for the analysis. That study generated three approaches: Front-end loading, Individual rate and Back-end loading methods.

Similarly, Picard, Antoniou and Adré de Palma (2010) carried a study on econometric model and developed canonic and hedonic price model. Regression model was used to generate hedonic regression model, the hedonic model was used in estimating demand and value of a specific good by decomposing it into its constituent characteristics. Hedonic models are usually estimated using regression analysis, however, more generalized models, such as sales adjustment grids, are special cases of hedonic models. The strength of hedonic model lies in capacity to accommodate non-linearity, variable interaction and other complex situations. Some of application areas of hedonic model include real estate application, real estate appraisals, computation of consumer price index (CPI) and relative price index (RPI) among others. In real estate economics, hedonic model is applicable in solving problem of price determination and price adjudication (Amusan et al., 2012). The model has capacity to accommodate heterogeneous variables such as those obtainable from building projects. Building project for instance involved several heterogeneous variables which tend to possess linear and non-linear relationships; hedonic model can combine such heterogeneous variables for meaningful deductions. Hedonic model according to Picard, Antoniou and Adré de Palma (2010) can treat the variables separately and estimate cost and prices (in case of an additive model) or elasticity in case of a log model). To this end, the econometric model developed in this study toe the line of submissions of Picard et al; (2010), that hedonic related model adopted cost entropy and econometric approach to generate a model that incorporates heterogeneous variable of residential project for price and cost judgment. It was discovered from the reviewed papers that applications have been centered around use of regression models, none has been used to develop prediction algorithm models, likewise combination of expert system and regression analysis has not been explored, this is a gap that this study assay to bridged.

1.5 Research Methodology

The objective of this study is to generate an exploratory study of cost modeling of residential building projects in Nigeria.

1.5.1 Data Source

One hundred (100) samples were picked at random from projects completed within the past four (4) years at selected locations: Ogun State, Lagos State and Federal Capital Territory (FCT) in Nigeria, these areas are regarded as economic nerve center and region of high construction activities (Ogunsemi and Jagboro 2006). Initial and final cost of the sampled projects were extracted and adjusted with price index to 2008 price and prevailing inflation index to be able to capture economic variable that influences building cost. Multi Layer Perceptron Neural network with Back Propagation system and Levenberg Marqua was used as configuration frame work, from Table 1.1 Thirty-six (36) percent of the samples was used in model testing, while fourteen (14) percent was used in model training for configuration.

1.5.2 Model Configuration Development and Validation

The method used in model generation in this study with Artificial neural network involves three (3) stages: the design, modeling (training) and cross validation stage.

1.5.3 The Design Stage: The first stage involves, the design of suitable neural network algorithm. Neural network architecture and Multi Layer Perceptron with Back propagation from Neuro Solution Software (MATLAB) were used to design a suitable algorithm.

1.5.4 Data Description: This study used cost significance work package in breaking down the project cost to their constituent's components. It involved combining the bill of quantities with similar description and construction methodology together into a package, this towed the line of submission by Rafiq et al., (2001) which finds base in

Pareto principle. However, in this context, the work package that belongs to 40% items with high cost) and 60% (items with low cost) were combined. This is to ensure a holistic estimation or prediction whenever the model is used.

1.5.5 The Modeling Stage: The adjusted initial and final construction cost were fed into the Multilayered Perceptron System with internal guiding principles and one layer. The principles includes: data characteristics, nature of problem, data complexity, and sample data. A number of hidden layers were selected after several iterations to obtain an optimum output. An optimized output was obtained after a stable and consistent output emerged. This is often determined by trials sine there is no rule to determine it. Further configuration parameters were set as presented in Tables 1, 2 and 3 the parameters include the means through which the data input, output error would be displayed, display format for performance matrix and validation window. These were set before the network building button was activated.

1.5.6 The Model Training Stage: The model was trained after configuration; the training was stopped when the mean square error was very low. The Back propagation technique was used in this context, since it tends to reduce error between model input and output. Back propagation method develops output from input while minimizing mapping error, that is, mean square error (MSE). This is given by the following relation.

MSE = [(square root of[((summation).sub(i=1) sup.n)[(xi-E(i)]sup.2])]/n ……….. 1

Where MSE = Mean square Error, n = number of projects to be evaluated at the training phase

[x.subi] = the model output related to the sample, E = target output. Mean square error is the measure of fitness of an output, the lower the figure the fitted the output. It is as well an index of training session success. The error was noted for each of the training epoch carried out, and was stopped when the value remain constant for a given iterations of epoch. This is to prevent technical dogmatism and output over fitting when the network is presented with unseen set of data.

The method above was used to synthesize an optimized cost after several iterations on neural network software, prediction algorithm was generated as presented in Fig. 2. The algorithm was ran mechanical with optimized cost fed into appropriate sections. There are three modules presented in the algorithm: the data optimization module, criteria selection module and initializing and terminating module. However, at the end of the loop an optimized cost in the form of predicted cost is generated. The algorithm could form further foundation for development of an hybrid software.

Table 1 Selection Criteria Matrix

Data Read From Existing file	Office Building
Percentage of Training Data for Cross Validation	20
Percentage of Data for Model Testing	40
Cross Validation Exemplar	20
Test Exemplar	80
Multilayer Perceptron Input	4
Multi Layer Perceptron Processing Elements	40
Multi Layer Perceptron Exemplars	62
Hidden Layer	1

Source: 2012 Survey

Table 2 Supervised Learning Control Attributes [Hidden Layers]

Input layer	Output Layer
Processing Elements: 22	Processing element: 1
Transfer Tanhaxon	Transfer Tanhaxon
Learning Rule Levenberg Marqua	Learning Rule Levenberg Marqua
Momentum Step Size:1.00	Momentum Step Size:1.00
Momentum Step Size 0.70	Momentum Step Size 0.70

Source: 2012 Survey Neuro Tool

1.5.7 The Testing Phase: Fourteen (14) percent of the remaining samples were used in model training.

Table 3 Active Cross Validation Performance for Office Building

Parameters	Active Cross Validation Performance	Cross Validation Performance
Mean Square Error	0.043	0.00035
Normal Mean Square Error	0.098	3546521.90
Regression Value 'r'	0.950	0.039

Source: 2012 Survey

1.5.6 Neural Network Algorithm Synthesized Output

The output of developed model is presented in Table 4

Table 4 Summary of Project Adjusted Bill of Quantity and As-built Value of Residential Building Projects (Millions of naira).

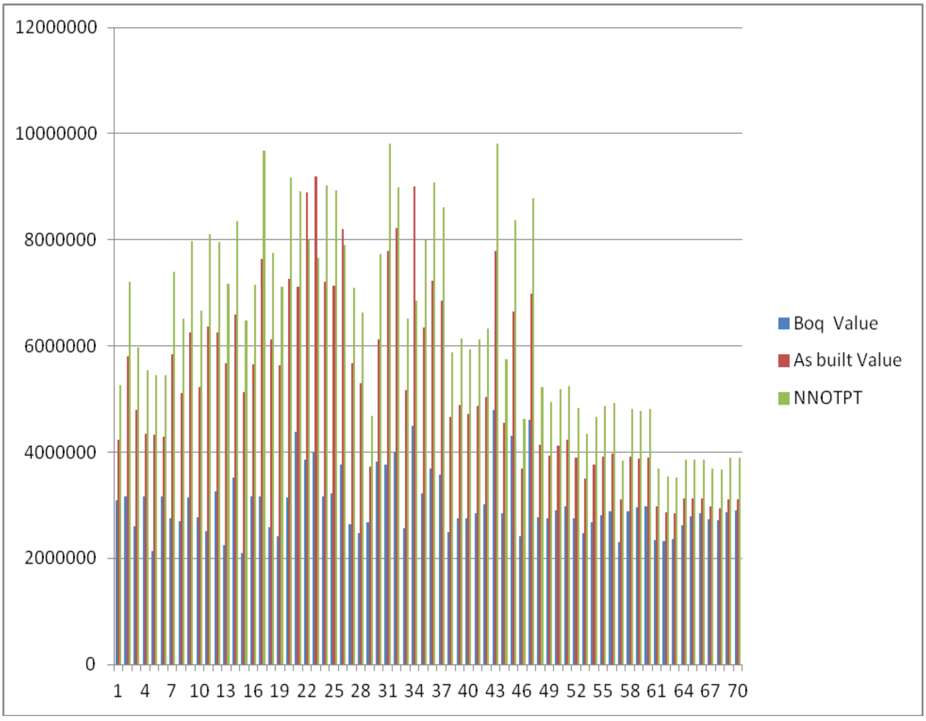
Period	Highest Initial contract sum	Highest as-built cost	Lowest init cont sum	Lowest as-blt	Highest variation	Lowest variation	Variation Range
2009	19,223,000	38,250,000	15,000,151	20,650,000	20,150,000	4,289,916	15,860,084
2008	16,044,130	30,763,000	11,300,000	12,214,000	14,753,000	6,083,000	8,670,000
2007	14,289,000	26,363,000	10,101,000	11,785,000	21,368,000	2,042,000	9,583,000
2006	13,000,000	24,000,000	8,000,000	8,500,000	9,422,000	2,435,000	6,987,000

Source: 2010 Survey

One hundred samples (100) of Residential buildings were used and categorized according to the period of execution that spans 2006 to 2009 as presented in Table 4. Highest contract sum was obtained among the projects executed in 2009 while the lowest was obtained among the 2008 projects with highest occurrence of variation noticeable in 2006 projects and lowest among 2007 projects. Economic meltdown could be adduced as responsible for trend. Radial diagram in Fig. 1 was used for visualization of synthesized output for the sampled office building projects.

1.5.7 Visualization of Input and Neural Input Pattern of 2 Bedrooms Bungalow

Distribution pattern of input and output cost data of 2-Bedroom Bungalow used in model generation is presented in the figure below:



Source: 2010 Survey

Figure 1: Bar- Visualization of Input and Neural Input of 2 Bedroom Bungalows

Legend**:** BOQ----- Bill of quantity. NNOTPT ----- Neural Network Output

Component bar chart is used in presenting the panoramic view of the cost distribution pattern of the three cost envelopes (the neural network predicted cost, as-built cost and bill of quantity value) is presented in Fig. 1 above. Highest neural network predicted cost was recorded within the cost range ₦9.4Million and ₦3.5Million. The range falls among projects completed between 2008 and 2009. Lowest as-built cost was N14Million during pre-economic meltdown and ₦26Million during post economic melt-down period. The base reference period used for prediction in this context is 7 months and with November 2010 as base month. Also, inflation index of 1.14% and corruption escalator factor of ten percent (10%) were used. These are however subject to change since the prevailing economic factor at the time of any cost prediction has to be taken into consideration.

1.5.8 Anaysis of the Developed Model

Stepwise regression analysis was carried out to investigate the relationship between a number of independent variables(initial contract sum, as-built sum and neural network output). The orrelation coefficient is presented in Table 5.

Table 5 Coefficients Matrix of Residential 2-3 -Bedroom Buildings Project

			Initailcontsum	Asbuiltsum	Neuraloutput
Kendall's tau_b	Initailcontsum	Correlation Coefficient	1.000		
		Sig. (2-tailed)	.		
		N	18		
	Asbuiltsum	Correlation Coefficient	.907**	1.000	
		Sig. (2-tailed)	.000	.	
		N	18	18	
	Neuraloutput	Correlation Coefficient	-.030	.160	1.000
		Sig. (2-tailed)	.909	.454	.
		N	18	18	18
Spearman's rho	Initailcontsum	Correlation Coefficient	1.000		
		Sig. (2-tailed)	.		
		N	18		
	Asbuiltsum	Correlation Coefficient	.987**	1.000	
		Sig. (2-tailed)	.000	.	
		N	18	18	
	Neuraloutput	Correlation Coefficient	-.047	.165	1.000
		Sig. (2-tailed)	.964	.597	.
		N	18	18	18

Source: Field Work 2012

Note: Correlation is significant at the 0.01(2-tailed).

Table 6 Summary of Analysis of 100 Samples of 2-3 –Bedroom Residential Building Project

Model	R	R Square	Adjusted R Square	Std. Error of the Estimate	Change Statistics				
					R Square Change	F Change	df1	df2	Sig. F Change
1	.980[a]	.987	.980	22.42611	.0045	0.000	2	15	.033

Correlation matrix in Tables 5 and 6 indicates value of Spearman and Kendalls tau Test. The analysis indicates perfect and positive correlation between neural output and initial contract sum. In spearman analysis while positive correlation exist between As-built sums, Initial contract sum
neural output is a little higher as a result of econometric factors added unto it. Generally, linear relationship exists among the two independent variables. Summary of collinearity statistics in Table 7 tolerance limit is large for the model variables; neural network output has value of 1.08 while contract sum has 1.00 tolerance values. In this model the two variables are regarded as very important.

Table 7 Regression Coefficients of the Developed Model

Model		Unstandardized Coefficients	Standardized Coefficients		t	Significance	Collinearity Statistics	
		B	Std. Error	Beta			Tolerance	VIF
1	(Constant)	4.1398	4.1587		9.953	.000		
	As built sum	-.908	.532	.995	-3.458	.051	1.00	1.00
	Neural network cost	.874	.397	1.788	3.945	.011	.904	1.45

Source: Data Analysis 2012 Notes: Dependent Variable: Neural Networks

1.5.9 Re-sampling

Re-sampling test was conducted on the model in order to ascertain the stability and the influence of outliers on the models' stability. The results are presented in Tables 7 and 8; two models are presented here, model of as-built sum and neural network model. Neural model has standard error of 0.197 while as-built sum model has 0.312. Generally the two models showed stability with high level of tolerance.

1.5.10 Cross Validation Test on The Model

Table 8 Collinearity Diagnostics[a]

Model	Dimension	Eigen value	Condition Index	Variance Proportions		
				(Constant)	As built Sum	Neural network Sum
1	1	3.923	1.000	.01	.00	.000
	2	.088	8.759	.58	.018	.045
	3	.087	16.995	.42	.030	.099

Source: Data Analysis 2012 a. Dependent Variable: Initial contract sum

The model is cross validated with the 40 samples, the validation results is presented in Tables 9 and 10.

Table 9 Model Statistics

Model	Number of Predictors	Model Fit statistics	Ljung-Box Q(18)		
		Stationary R-squared	Statistics	DF	Sig.
Asbuiltsum-Model_1	1	.0097	.000	0	.000
Neural Network-Model_2	1	.065	.000	0	.000

Table 10 Model Fit

Fit Statistic	Mean	Square Error	Minimum	Maximum
Stationary R-squared	.031	.029	.006	.031
R-squared	.035	.058	.000	.078
Root Mean Square Error	7.1267	3.5237	7.5427	9.9527
Mean Average Percentage Error	20.185	4.9898	37.412	33.892
Maximum Average Percentage Error	90.213	.912	91.000	92.801

Table 11 Summary of 100 sampled 2-3 -Bedroom Residential Buildings.

Project	A	B	C	G	E
	Bill of Quantity Value	As Built Value	Inflation Adjusted Factor	Neural Network Output	Variation Quotient
1	3085100	4236000	0.0114	5,272,837	0.271278416
2	3171800	5800000	0.0114	7,219,654	-0.07403271
3	2610000	4800000	0.0114	5,974,886	0.666390707
4	3165000	4350000	0.0114	5,535,606	0.141994176
5	2145000	4325000	0.0114	5,455,724	0.440230229
6	3174953	4286350	0.0114	5,454,607	0.458244508
7	2750000	5850000	0.0114	7,392,422	0.074005971
8	2700850	5121000	0.0114	6,516,743	0.48622077
9	3150000	6265000	0.0114	7,972,545	0.260012712
10	2766000	5223000	0.0114	6,669,763	0.543991808
11	2510000	6371000	0.0114	8,107,435	0.53806336
12	3268000	6250000	0.0114	7,953,456	0.287403351
13	2250325	5675000	0.0114	7,177,588	0.367504287
14	3520000	6600000	0.0114	8,347,503	0.541092931
15	2100000	5125000	0.0114	6,481,963	0.101308513
16	3173000	5652000	0.0114	7,148,498	0.537486305
17	3173000	7650000	0.0114	9,675,515	0.383159104
18	2580315	6131000	0.0114	7,754,324	0.342966833
19	2420500	5643000	0.0114	7,112,028	0.301008209
20	3143000	7266000	0.0114	9,173,691	0.521656598

21	4385500	7121000	0.0114	8,919,392	0.102080487
22	3867620	8900000	0.0114	7,987,634	0.092721675
23	4010850	9201000	0.0114	7,654,136	0.456341114
24	3172771	7213000	0.0114	9,034,627	0.2511614

Source: Data Analysis 2012

Forty(40) samples of one hundred (100) projects executed in 2009 were used in the model cross validation to ascertain the accuracy level, according to the analysis of report presented in Tables and 10 and 11, -0.07403 lowest variation quotients to 0.893467812 highest variation quotients are obtained. Also the Regression coefficient (R-square) value for determining the model fitness is 0.035 with standard error of 0.397 this indicate a good level of fitness.

1.5.11 Discussion

Specifying variation error and prediction error determination is an important step in regression modeling. The results of analysis presented give an indication of validity expectation of the model. Regression analysis conducted through the Jackknife technique also produced results revalidating stability verdict earlier obtained at network configuration stage. This method is deployed to ascertain how the model will perform when influenced by new set of variables. Also, at all the stages, neural output has shown stable and consistent output when compared with as-built cost of projects.

1.5.12 Conclusion

A neuro-regression model of residential building work is presented in this study. The model is flexible in accommodating new data and variables, thus, it allows for inclusion of new variables. Neural network was used to generate the model algorithm, the algorithm is divided into three(3) modules: the data optimization module, criteria selection with initializing and terminating modules. Also, some of the model parameters include; bill of quantity value of a project, as-built sum and neural network generated output.

After configuration, the network was used to process data of residential building works. The neural output represents a predicted cost range for the office projects with regards to prevailing economic situation like inflation and building price index, this was factored into the as-built cost of the project and predicted upward for the period of six (6) months. Thus the specified range of prediction expressed for the model is six (6) month subject to constant economic variables; however, if economic variables change before the six month prediction window period, the cost should be adjusted with the current economic variables. Cross validation analysis indicates -0.07403 lowest variation prediction quotients to 0.66639 highest variation quotients. Also the Regression coefficient (R-square) value for determining the model fitness is 0.035 with standard error of 0.397 these variables are often used as index to measure model fitness, this, however, tows the line of submission of Li Heng, Shen Q.P and Love Peter (2005) that a valid regression model should have regression co-efficient value between 0.025 to 0.050 with error within 0.50 upper limit.

16. Contributions

i. The study has demonstrated the applicability of building informatics in solving cost problem in building; this was validated by the model generated in this study.
ii. The model generated it has capability of helping constructors predict the construction cost in advance of actual commencement period.
iii. Builders can load implication of unseen quantifiable economic variables and environmental variables on the model to determine actual amount to budget for their building works.
iv. Implication of this on researcher is that the model has laid a foundation for development of software that explores the neural network and regression analysis.

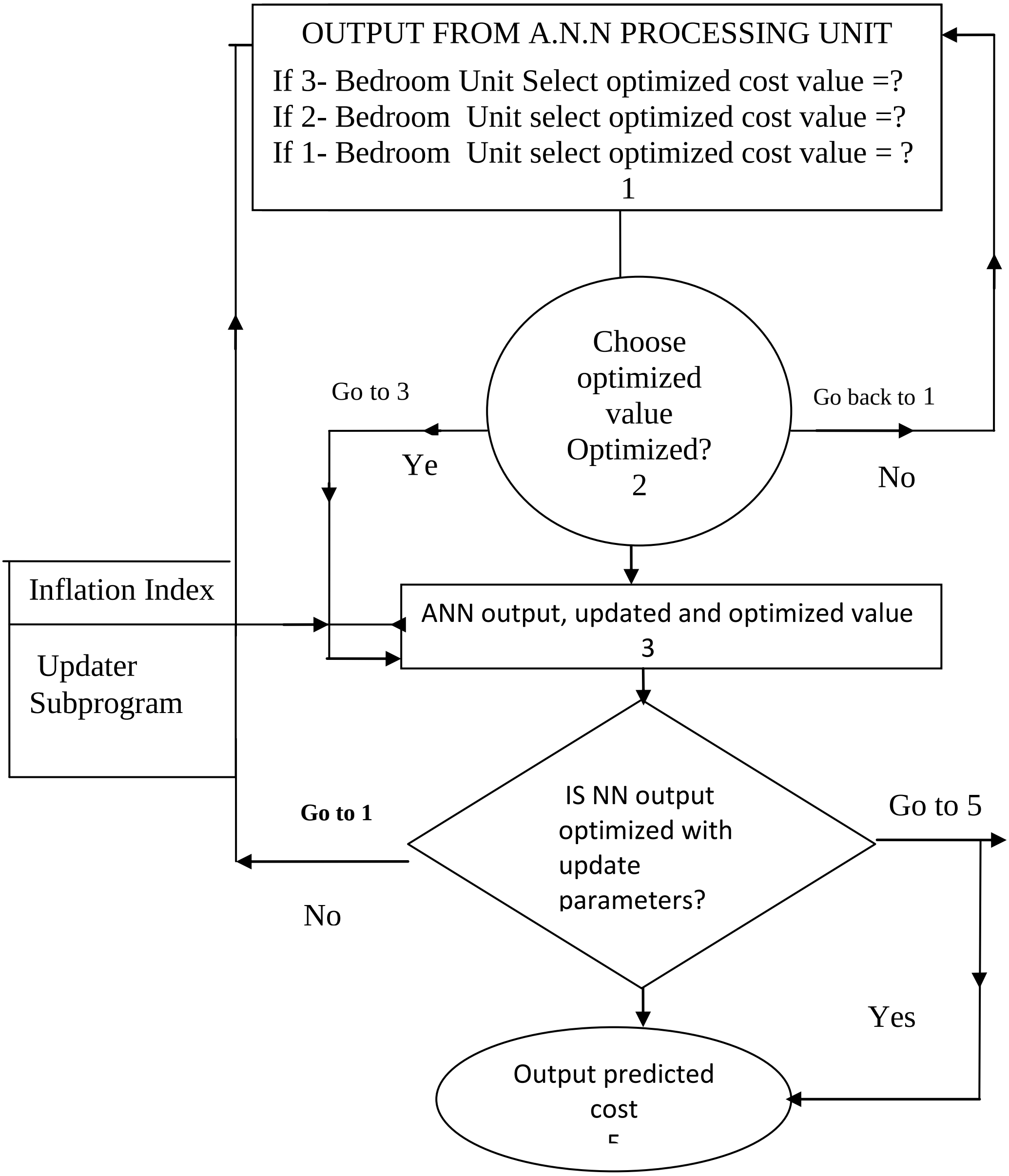


Fig. 2 Residential Building Construction Cost Prediction Algorithm

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