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# Acceptance of paper #310 for 23rd IBIMA Conference

1 message

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Dear Dr. Amusan Lekan, Dr. Fagbenle Olabosipo, Dr. Mosaku Timothy, Dr. Ayo Charles, Dr. Owolabi Dele, Dr. Omuh Ignatious, Dr. Tunji-Olayeni Patricia, Dr. Ogunde Ayodeji and Dr. Peter Joy,

Congratulations! I am pleased to inform you that your paper submission "Neural Network and Econometric-Based Utility Parameter Model for Cost Management of Building Projects," to the International Business Information Management Conference (23rd IBIMA) on 13-14 May 2014 in Valencia, Spain has been accepted for presentation at the conference. The paper will be included in the conference proceedings (ISBN:978-0-9860419-2-1) as a full paper.

The paper, after addressing review comments, is recommended for "Journal of South African Business Research" OR "Journal of Economics Studies and Research," published by IBIMA publishing. Journals website: http://www.ibimapublishing.com

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Attached to this e-mail:

1) Camera ready format guidelines for 23rd IBIMA (in Microsoft word)
2) IBIMA Publication agreement (in pdf)
3) Registration form
4) IBIMA publishing Publication agreement (in case you choose to proceed for journal publication as well)
5) Summary of review

Conference Hotel information will be available soon online. www.ibima.org

At this time, please make sure that you take care of the following details:

1. Please provide your final Submission (in Microsoft word format) electronically to me by 30 April 2014. Make sure to follow the attached guidelines in preparing this document. Please be sure to include the reference #310 in the subject line of your email when you send the paper.

2. We encourage all authors of the paper to register for the conference by the registration deadline of 30 April 2014. However, in order for the presentation to be included in the conference and the proceedings, one author must register by 30 April 2014.

3. A registration form is attached. Please fill it out and mail OR Scan & e-mail OR fax to the International Business information Management Association (IBIMA) together with your payment.

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We look forward to your participation in this major international event conference

Sincerely,
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23rd IBIMA Conference Chair

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**IBIMA CONFERENCE 2014**

**NEURAL NETWORK AND ECONOMETRIC-BASED UTILITY PARAMETER MODEL FOR COST MANAGEMENT OF BUILDING PROJECTS**

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Abstract

The aim of the study is to develop a project cost centre utility parameter-based econometric model that incorporates econometric parameters using neural network. Construction cost of residential building projects was used in this study. Random sampling technique was used to select projects completed between 2009 and 2011, and were examined for their cost centres validity. Final construction cost (As-built cost) of selected four hundred (400) projects were further modified with econometric factors like inflation index, cost entropy and entropy factor and were used to form and train neural network Back propagation neural network algorithm used. Probability technique was used to generate risk impact matrix and influence of entropy on the cost centres. In this study a parametric model similar hedonic models was generated using the utility parameters within the early and late elemental dichotomy. The developed model was validated through comparative analysis of the econometric loading attributes of the variables involved, using Monte Carlo technique of SPSS software by extracting the resultant contingency coefficient. This attribute would help client, project team and contractor manage cost of construction, also, it would enable a builder or contactor load cost implication of an unseen circumstance even on occasion of deferred cost reimbursement and help

Keywords: Neural network, Model, Propagation, Econometric, Escalator, Risk, Dichotomy, Entropy.

## 1.1 Introduction

Managing construction cost on site is an important phase of project life cycle. It enables early detection of problem area that may hinder timely project completion and adequate fund flow. However, mistake on cost issues at planning state can jeopardize the expectation of clients in obtaining value on money invested on one hand and project team on the other (Mosaku and Kuroshi 2008). Sometimes mistake in cost management on site as resulted in cost overrun, and many promising project has become a white elephant projects and a great deal of effort had gone into researchers evolving a system that would provide good cost management and decision system, and harmonize needs of project participants. It has been discovered that good cost management or judgment in cost allocation would ensure effective spreading of fund across all the project elements, this in turn would ensure consistent fund availability even on occasion of delay in fund disbursements by the client (Amusan et al; 2012). However, error of judgment often arises out of use of inadequate tool in generating cost detail. Therefore a system that accommodates unforeseen intervening variables that often accounts for cost variation that could facilitate meaningful cost pattern deduction in project cost monitoring and project cost progress evaluation is highly essential (Amusan et al; 2012). It is to this end that this study developed an econometric cost management and decision system for residential building works using expert system approach and cost entropy patterned in hedonic form. This model provides for incorporation of cost variants into project' cost in order to buffer the effect of possible delayed payment on a project. The model developed in this context is similar to hedonic models and canonic models which uses parametric estimation method in solving problems. Hedonic models are often used, when testing parameter is heterogeneous in nature; it facilitates according individuality to constituent parameter of test variables by highlighting their utility function. Constituent parameters are often treated with respect to their contributions to the test variables; likewise environmental parameters that have potential to influence final computation of test variable are often studied within the context of their peculiarity and often factored into test variable for holistic computation. The purpose of this paper therefore is to apply the strength of parametric model to generate a model that could accommodate heterogeneous parameters such as those obtainable in an econometric situation, and accord individuality to constituent parameters to generate a conventional model for cost management and decision in building construction.

Therefore, in this study, the following interesting aspects were introduced: theory of hedonic model that formed the background of parametric estimation, bid-balancing models, application of expert system, entropy application in measuring project cost dynamic, project risk matrix and factoring of intervening variables that influences cost into the project cost main stream. The idea behind the study is to use neural network and econometric-entropy to develop a utility parametric model that could be used in project cost decisions and management.

**1.2 Review of Related Literatures**

Cost center in construction parlance refers to project elemenst arranged in logical manner that favours cost allocation, therefore, uniqueness of a 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 balancing or cost judgment.

Furthermore, a cost decision can be the type that favours upward 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, paradigm has shifted as a matter of necessity 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. One of such models is Bid-balancing , the model modifies cost either in reverse order or forward other. 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) description, is the process by which intelligent approach is used in evenly distribution of overall project actual cost and profits among project activities without jeopardizing the total bid price for the work.

In a related study, Picard, Antoniou and Adré de Palma (2010) carried a study on econometric model and developed canonic and hedonic price model. The study used regression model to generate hedonic regression model, hedonic model was used in estimating demand and value of a specific good by decomposing it into its constituent characteristics. The estimate of contributory value of the constituents was aided by hedonic regression price model.
Ideally, 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 on 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 the study can treat the variables separately and estimate cost and prices (in case of an additive model) or elasticity in case of a log model).

For instance, 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 the study; cost centres of the projects on bill of quantity were classified into two groups and used for the analysis. The study generated three approaches to bid-balancing model generation for risk identification. The methods include: Front-end loading, Individual rate and Back-end loading method.

To this end, the econometric model developed in this study toe the line of submissions of Picard et al; (2010), the hedonic related model adopted cost entropy and econometric approach to generate a model that incorporates heterogeneous variable of residential project for price and cost decisions.

Similarly, Cattel, Bowen and Kaka (2008) developed a hedonic related econometric model which was used in unbalanced bidding. The study presents different schools of thought in the study of unbalanced-bidding in line with submissions of Stark (1972). Cattel, Bowen and Kaka (2008) described available methods as Back-end loading, Front-end loading and Individual rate loading systems. According to the study, Front-end loading method, is used to mark up of items scheduled to come up early at beginning of the project as high as possible in order to provide avenue for builders to generate as much profit as could help in further project financing. The method is described by the following mathematical model.

$\mathrm{pvj} = \sum_{n=0}^{N} \left(\frac{1}{1-r}\right)^{n} [\lambda njQj\,(Pj - Cj)]]$(Cattel et al., 2008).

Back-end loading system involves marking up prices of project items that is billed to be executed later on the project (Cattel et al., 2008). It was described as method that over overcompensates a project builder or contractor for inflationary increases, consequent upon inflationary buffer already built into the project cost package as contained in the projects' documents. This is described by: $\mathrm{pvj} = \sum_{n=0}^{N} \left(\frac{1}{1-r}\right)^{n} [\lambda njCj\,(Pj - Cj)]]$(Cattel et al., 2008).

The third method is Individual rate loading method. In this method, it is common practice to load profit margin high, by individually loading the project elements with additional cost to cushion negative effect of price fluctuations. It entails loading cost component of project components that has tendency to increase later as the project progresses while marking low the components that could be executed early on the project. This is described by the model below:

$\mathrm{pvj} = \sum_{n=0}^{N} \left(\frac{1}{1-r}\right)^{n} [\lambda njQj\,(Pj - Cj)]]$(Cattel et al., 2008)

Legend: Pv—present value; j ---item number; N– duration of project; n --- number of months; rj – monthly discount rate; Qj – Bill of quantity of an item; Pj – bill price per unit of item j, Cj – unit price per unit of item.

Moreover, Rosen (1974) formulated basis for hedonic models, the study was used for simultaneous estimation of demand and supply and simulate them with market demand, the study assumes that goods are valued for their utility bearing attributes. Rosen's hedonic model is composed of two parts, the marginal implicit price calculation unit and marginal prices and consumer socio-economic climate segment. Among other things, the model has the following assumptions: homogenous market and price flexibility to forces of demand and supply. However, the approach was opposed by Brown and Rosen (1982), the approach according to the researchers tend to impose homogeneity of characteristics across individual variables thus encounter identification problem. Brown and Rosen (1982) suggested in their submissions, incorporating of economic variants in to the model in order to accord individuality to each constituent variables of parameter being measured.

Similarly, Bajari and Benkard (2004), studied demand estimation with heterogeneous consumers and un-observed product characteristics using hedonic approach. Bajari and Benkard's model allows for individual variable in the unit being measured to have different utility parameters but with parametric restriction on utility function. This approach provided solution to identification problem encountered by Rosen (1982) by allowing individual variables an opportunity to have different utility parameters which further consolidate the findings.

In another related study, Bajari and Kahn (2005) used hedonic approach in estimating housing demand, which is linked with racial segregation in big American cities. The study presents a three- stage nonparametric estimation procedure to recover willingness to pay for housing attributes. Local polynomial function was used in formulating stage I, stage II by first order conditions for utility maximization while, stage III estimates the distribution of household taste as a function of household demographics. The empirical model developed by the model is innovative in the sense that it added the dimension of heterogeneity to the price adjudication system.

In the context of model proposed in this study, however, theory underlined approaches presented in the reviewed submissions of Rosen (1974); Brown and Rose (1982); Bajari and Benkard (2004); and Cattel, Bowen and Kaka (2008) were adopted in generating a price modification model presented in this study. The model accords individuality to the constituent parameters that makes up a project, to achieve this, the cost centres were treated without restrictions on their utility function thereby accord them different and distinct utility parameters. This approach enables easy evaluation of the model's economic parameters and loading of economic variants like cost entropy margin, inflation index and exigency factor ( similar to Haylet factor like those used on South African projects as discovered in Cattel et al; 2008).

Furthermore, Bouabaz and Hamani (2011) carried out a study on generating cost estimation model for repair of bridges using artificial neural network. The study used genetic algorithm for data mapping, cost of bridge component were used as cost centre, the model generated has mean average error of 0.36 between every output and input, according to the authors, the model has cost estimating ability with minimum error.

Similarly, Chao and Skibnieswski (2011) evolved an expert system based model in a study on application of estimating strategy on construction project cost prediction. Neural network system was used to generate a model that has ability to predict cost of construction projects. The model used back propagation neural network that maps output with input to generate a logic algorithm. The model was tested on data from cost centers of construction projects. The model has Minimum average Error of 7% between input and predicted value.

In a related study, Gouda; Danaher and Underwood (2012) studied application of artificial neural network in modelling thermal dynamic in building with a view to developing heat movement matrix for a building type. Residential building spaces in Texas were used in the study. The study generated heat movement data through measuring emitted heat from surfaces of features in building. The study was limited to selected types of building space based on space configuration. A model of expected heat matrix was generated for building spaces and residential building used.

Moreover, Kiang; Fisher; Hu; and Choi (2013) investigated the application of Neural network in generating a viable neural network prediction model. In the study, an extended self organizing map network was generated, the model is capable of being used in forecasting market segment membership. Data of membership of various market groups was used, the membership was categorized into segments and pattern of membership studied over a period of 6 years. A network algorithm synchronizing bench marked pattern with emerging trend was generated. The model generated could help in monitoring stock trade transactions and movement of customer along the line of stock purchase.

### 1.2 Method Statement for the Research

Background has been provided for study within the context of related previous works in order to position this study in the light of previous researches conducted in the econometric approach in model generation. Econometric approach was used to generate model in this context, it follows the order of Hedonic models presented by Rosen (1974); Bajari and Kahn (2005); Bajari and Benkard (2010); and Picard, Antoniou and Andre de Palma (2010). The model adopts hedonic style with parametric equations that incorporate and accord individuality to the project cost variables and test parameters. The As-built costs of the projects were stabilized with inflation buffer, exigency factor and risk index, and were loaded to neural network for further stabilization. Influence of elemental cost on project cost and project cost entropy was determined as well as the risk impact matrix for the selected projects. Also, the modified As-built cost of the sampled building projects was modified and processed to obtain an optimal cost, the optimal cost was used to generate the model in this study. The generated parameters (risk matrix, cost entropy, exigency factor, neural network stabilized optimum cost) were factored into the expert-system and econometric model generated, the model is similar in attribute to back-end loading hedonic model of Cattel et al; (2008).

### 1.3 Research Methodology

Residential building projects were randomly selected for analysis. Thirty-five residential building projects were analyzed in the following order; 2/3 –Bedroom unit (11 samples), 4-Bedroom Duplex (12 samples) and 2&3-Bedroom bungalow (12 samples). The bill of quantities' contents was validated through content analysis, content analysis method was used to extract component cost and validate inter-cost centre relationship. Analysis was carried out on the sampled projects, the following activities were carried out: factoring of cost centre influence on total project cost; determination of monetary-entropy; risk impact matrix formulation based on entropy level; project monetary dynamics; comparative analysis of different bid-loading system and synthesization of neural network-econometric parameters-based tender adjudication system using back-end loading as base reference. Suitability of the developed neural network-econometric model was validated within the context of late constructible element cost loading and individual cost loading with the aid of contingency coefficient, Kendal Tau values and Monte-Carlo comparison techniques. Also, entropy state of the project elements was generated using probability estimation method.

### 1.3.1 Data Training Using Artificial Neural Network:

**a. The Training Stage:** The training data set (300 samples) of residential building projects of 400 projects having being modified with inflation index and exigency factor, was used to train the multilayered perceptron neural network selected, so as to select its parameters, the one suitable to problem at hand. Back propagation was used to train the network since it is recommended and simple to code. So also gradient descent momentum and learning rate parameters was set at the start of the training cycle (for speed determination and network stability, range of momentum $0.1 \leq x \leq 1$, high = weight oscillation coefficient). Back propagation algorithm involves the gradual reduction of the error between model output and the target output. It develops the input to output, by minimizing a mean square error (MSE) cost function measured over a set of training examples. The M.S.E. is given by this relation:

*M.S.E = [( square root of [[[summation). Sub. (i=1). Sup.n) [(xi – E (i)].sup.2]]]* $/_n$

Where n is the number of projects to be evaluated in the training phase, [X.sub.i] is the model output related to the sample, and E is the target output. The mean square error is an index of successfulness of a training exercise. The error was measured for each run of the epoch number selected; however training was stopped when the mean square error remains unchanged for a given number of epochs. This is to avoid overtraining, and technical dogmatism when presented with an unseen example (data).

**b. The testing phase**: Data from remaining 100 samples of 400 samples were used as testing data set to produce output for unseen sets of data. A spreadsheet simulation program on Microsoft excel was used to test the generated model, according to optimized weights, comparison was made between actual cost and neural network cost, using cost percentage error (CPE) and mean estimated error (MEE).

CPE = [[Enn – Bv]/[Bv]] × 100%

MEE = [ $1/_n$ ][[ I = n]. summation over (i = 1)] cpe(i)

### 1.4 Data Analysis and Presentation

The presentation in this section follows the following order: factoring elemental cost centers percentage influence on project cost, entropy and risk threshold perspective on project cost( cost and risk impact prediction matrix), determination of project monetary entropy within the context of late and early constructible elements' monetary entropy for sampled residential buildings, structural component of neural network econometric modified back-end loading model, validating neural network econometric entropy- based model using comparative analysis of the econometric loading attributes and cost limit.

#### 1.4.1 Factoring Elemental Cost Centers Influence on Project Cost

Entropy is considered a measurable concept; it is the function of inverse of probability of variable in consideration (Choi and Russell 2010; Ajibade, A.A and Thomas P. 2008). This is linked to influence of cost centers on final cumulative as-built cost of a project. Quantitative analysis of cost influence on total as-built cost of selected residential accommodation was carried out and presented in Table 1.1 with a view to determining entropy state of the project cost centers.

In this section, influence of cost centre on project cost was quantified; by dividing each cost center weight by cumulative cost of the cost centers of a particular project, this was carried out through quantitative analysis of cost component of sampled residential building projects bill of quantities. The elemental cost component used for this purpose is presented in the Table 1.1, while the approach used here is in line with presentations in Choi and Russell (2005) and Christodolou (2008).

Influence of the elements' cost on total project cost was factored on rating scale one (1) to ten (10) using individual cost composition as base reference point. Cost of substructure for 4-Bedroom Duplex, 2/3 -Bedroom bungalow, Frame and walls were rated high on scale $10^+$ high relative to base cost, for all building types. Finishing is ranked high on scale $10^+$, for 4-Bedroom Duplex, 1-Bedroom apartment, 3/4 –Bedroom on 3 Floors-24 Units and 2/3-Bedroom Bungalow. This indicates that the influence of this is high on the project final cost. The implication of this is that a great deal of resource is at stake on this particular element, careful management of this cost centre can determine to a very large extent the overall success of the project work. Value added Tax, Contingencies, Preliminaries, Soil drainage; Fittings were rated low on scale 4 down to 1. However, this does not mean they are the least in term of importance, they as well has contributory effect on the total project cost. Ideally, one would have been tempted to select those cost centers with high rating and high risk index as the core parameters and prorate the remaining elements; danger in this option lies in imbalance cost composition that could arise as the consequence. Therefore in bid adjudication, cost of elemental components with high influence factor should be considered first and ensure adequacy since they attracts higher risk. Contingency can be built around them to cushion effect of eventuality.

**Table 1.1: Factoring Elemental Cost Centers Influence on Project Cost**

| S/N | Elements | Cost Rating On Scale ( 1) To Ten (10 ) | | | |
|---|---|---|---|---|---|
| C. | | 4-Bedroom Duplex | 2/3- Bedroom Bungalow | 1- Bedroom Apartment | 3&4-Bedroom, 4 Floors |
| ELT1 | Substructure | $10^{+4}$ | $10^{+12}$ | $10^{+19}$ | 8 |
| ELT2 | Frame & Walls | $10^{+9}$ | $10^{+3}$ | $10^{+2}$ | $10^{+25}$ |
| ELT3 | Stair Cases | 2 | --- | --- | 3 |
| ELT4 | Upper Floor | 9 | --- | --- | 4 |
| ELT5 | Roofs | 7 | 10 | $10^{+4}$ | 4 |
| ELT6 | Windows | 5 | 4 | 5 | 5 |
| ELT7 | Doors | 6 | 5 | 5 | 5 |
| ELT8 | Finishing | $10^{+4}$ | $10^{+12}$ | $10^{+10}$ | $10^{+5}$ |
| ELT10 | Fittings | 2 | 3 | --- | 6 |
| ELT11 | Services | 7 | 7 | 6 | 7 |
| ELT12 | Soil Drainage | 2 | 2 | 7 | 6 |
| ELT13 | Preliminaries | 4 | 4 | 5 | 7 |
| ELT14 | | 3 | 2 | 3 | 3 |

| | | | | | |
|---|---|---|---|---|---|
| | Contingencies | | | | |
| **ELT15** | Value Added Tax (5%) | 5 | 5 | 5 | 1 |

Source: 2011 Survey

### 1.4.2 Entropy Level and Risk Threshold Perspective on Project Cost

The risk associated with project cost center can be quantified in term of degree of uncertainty,( probability of occurrence and magnitude of impact( i.e on project objective, quality and time). However, in simpler terms, a criterion value, ranking or status for each risk event (or set of combined events) may be established by dividing the frequency of relevant events by total number of possible events. In this section therefore, according to Amusan et al; (2012), a planner should consider both financial assignment that will minimize project risk and maximize cost and also financial assignment that will maximize profit and prevent project disarray. Therefore at tender stage, elemental components with high risk factor should be considered first since they attract higher risk. Analysis of risk distribution on three different types of projects is presented in Table 1.1 with a view to developing cost and risk impact probability matrix for the project. The risk probability value for cost centers of the project was quantified by dividing cost of individual component with total cost of all components and presented on scale 0 to 1.

**Table 1. 2: Cost and Risk Impact Prediction Probability Matrix**

| PROBABILITY | **4 -bedroom Duplex** | **2&3-bedroom Bungalow** | **1-bedroom Apartment** | **3 /4-bedroom, 24 Units 4 Floors** |
|---|---|---|---|---|
| EXTREME 9-20 | 14(1.4Sub)<br>15(1.5Finish)<br>19(1.9Frame)<br>7(0.7Serv)<br>9(0.9Uppflr)<br>7(0.7Roof) | 13(1.3Sub)<br>13(1.3Frame)<br>10(1.0Roof)<br>12(1.2Finish) | 20(2.0) Finishing)<br>19(1.9 Substruct)<br>12(1.2 Frame)<br>------<br>-------<br>14(1.4Roof) | 20$^{+}$ (2.0) Frame<br>15(1.5 Finishing) |
| HIGH 6-8 | 5(0.5Wind)<br>6(0.6 Doors) | 7(0.7Services) | 6(0.6Services)<br>7(0.7Soildrg) | 8(0.8 Sub )<br>6(0.6 Fittings)<br>6(0.6 Soildrhg))<br>7(0.7 Services)<br>7(0.7 Services) |
| MEDIUM 3-5 | 3(0.3 Contig)<br>4(0.4 Prelm)<br>3(0.3 Contg) | 3(0.3 Fittings)<br>5(0.5 VAT)<br>4(0.4 Wind )<br>5(0.5 Doors)<br>4(0.4 Prelim) | 5(0.5 Window)<br>5(0.5 Prelim)<br>3(0.3 Doors )<br>5(0.5 Soildrg)<br>5(0.5 VAT) | 3(0.3 Staircs)<br>4(0.4 Upperflr)<br>4(0.4 Upperflr)<br>5(0.5 Windw)<br>5(0.5 Doors)<br>3(0.3 Contig) |

| | | | | |
|---|---|---|---|---|
| LOW 0-2 | 2(0.2 Stair) | 2(0.2SoilDrain) | | |
| | 2(0.2 Soildrg) | 2(0.2Conting) | | |
| | 2(0.2 Fittgs) | | | |
| | 1 | 2 | 3 | 4 |

IMPACT/CONSEQUENCE Source 2011 Survey

The risk range suggested here are tagged as low, medium, high and extreme cases. High and extreme is tagged as risk range between 0.5 and 0.8; medium 0.3 to 0.5, low is branded as risk between 0 and 0.2 while extreme risk falls between 0.9 and greater than 9.

When quantifying entropy state of project cost elements, in order to determine price movement pattern (entropy state) in a project collection, certain tri-partite variables should be considered keenly. The tri-partite variable refers to money, risk, and time. Entropy state of the tripartite concepts can be quantified as demonstrated in this study. Risk entropy therefore was quantified so as to know the risk activeness of the project cost centres. Cost centres of selected building projects were analyzed for risk implications. Risk is categorized into low medium and high scale as contained in Table 1.2. The risk component is presented on scale 0-20. Risk range 9-20 is regarded as Extreme, 3-5 as Medium, 6-8 as high. The following centres belong to the extreme risk imparted class: 4-Bedroom Duplex, 2&3-Bedroom Bungalow, 1-Bedroom Apartment, 3 /4-Bedroom, 24 Units on 4 Floors. Cost centres with Extreme risk threshold includes: 14 (1.4Substructure), 15 (1.5 Finishing), 19 (1.9Frame), 7 (0.7Services), 9 (0.9Upper Floor), 7 (0.7 Roof), 20 (2.0) Finishing) and $20^{+}$ (2.0) Frame.

Entropy in the real sense of it is a measurable concept; this is regarded as a function of inverse of probability of variable in consideration. This is linked to influence of cost centres on final cumulative as-built cost of a project. Quantitative analysis of cost influence on total as-built cost of selected residential accommodation was carried out and presented in Table 1.1 with a view to determining entropy state of the project cost centres. In this section, influence of cost centre on project cost was quantified; this was carried out through quantitative analysis of cost component of sampled projects bill of quantities of some selected residential building projects, which were used in model development. The elemental cost component was used for this purpose and is presented in the Table 1.1. Influence of the elements' cost on total project cost was factored on rating scale one (1) to ten (10) using percentage cost composition as base reference point. Cost of substructure for 4-Bedroom Duplex, 2/3 -Bedroom bungalow, Frame and walls were rated high on scale $10^{+}$ high relative to base cost, for all building types. Finishing is ranked high on scale $10^{+}$ 4-Bedroom Duplex, 1-Bedroom apartment, 3/4 –Bedroom on 3 Floors-24 Units and 2/3-Bedroom Bungalow, this indicates that the influence of this is high on the project final cost. The implication of this is that a great deal of resource is at stake on this particular element, careful management of this cost centre can determine to a very large extent the overall success of the project work. Value added Tax, Contingencies, Preliminaries, Soil drainage; Fittings were rated low on scale 4 down to 1.

However, the items rated low are not the least in importance among project elements, they as well has contributory effect on the total project cost. Ideally, one would have been tempted to select those cost centers with high rating and high risk index as the core parameters and prorate the remaining elements; danger in this option lies in imbalance cost composition that could arise as the consequence. Therefore, in some of the models studied so far, bid evaluation model cost of elemental components with high influence factor were considered first since they attracts higher risk. In this sense, contingency could be built around them to cushion effect of eventuality (Bromilow, F.J.,Hinds, M.F. and Moody,N.F. 1988; (Amusan et al; 2012).

### 1.4.3 Evaluating Project Cost monetary Entropy

Cost distribution pattern emerged in the analysis presented in Table 1.2 and 1.3. It follows a pattern of law of inverse proportions. The lower the cost variation the lower the degree of probability variations produced, and consequently the lower the entropy and vice versa. The entropy mentioned here is the index used to quantify the degree of cost restiveness on the project. The movement could be traced to incessant price changes on account of macro and micro economic variables.

The projects used in this work were executed during the economic meltdown period; this is adjudged as one of the factors that could lead to the price movement and disparity in cost-entropy obtained. The dynamic nature of price movement in a project being executed often dictates the pace of entropy magnitude. It is believed the greater the price movement and the higher the entropy that will be generated. Twenty projects were selected for illustration the cost movement pattern as discussed; Tables 1.3 to 1.4 illustrates the cost distribution with corresponding monetary entropy schedule and their implications on projects.

**Table 1.3 Summary of Adjusted Projects B.O.Q Value and As-built Cost of 4-Bedroom Duplex Year 2006-2009.**

| | | 1 | 2 | 3 | |
|---|---|---|---|---|---|
| | Project | A | B | C | |
| **Cost Centers** | | B.O.Q Initial Value | As-Built Cost | Cost Vartn | Perct g |
| **Project 1-11** | 1 | 16,043,869 | 22,676,000 | 6632131 | 29 |
| **Residential** | 2 | 16,500,603 | 23,565,000 | 7064397 | 30 |
| **Building** | 3 | 16,225,501 | 24,113,000 | 7887499 | 33 |
| **2009** | 4 | 16,400,521 | 27,654,000 | 11253479 | 41 |
| | 5 | 17,100,438 | 22,221,000 | 5120562 | 23 |
| | 6 | 17,300,113 | 28,450,000 | 11149887 | 39 |
| | 7 | 16,800,073 | 30,500,000 | 13699927 | 45 |
| | 8 | 17,220,134 | 26,350,000 | 9129866 | 35 |
| | 9 | 16,210,687 | 25,800,120 | 9589433 | 37 |
| | 10 | 18,500,936 | 23,450,000 | 4949064 | |
| | 11 | 16,360,084 | 20,650,000 | 4289916 | 21 |

**Table 1.4 Table Cost Schedule for 2-Bedroom Bungalow**

| | | 1 | 2 | 3 | |
|---|---|---|---|---|---|
| | Project | A | B | C | |
| **Cost Centers** | | B.O.Q Initial Valuet[Tender cost] [₦] | As-Built Cost [₦] | Cost Variation(B-A) [₦] | Percent Var |
| **Project 1-20** | 1 | 3,085,100 | 4,236,000 | 1,150,900 | 36 |
| **Residential** | 2 | 3,171,800 | 5,800,000 | 2,628,200 | 83 |
| **Building** | 3 | 2,610,000 | 4,800,000 | 2,190,000 | 84 |
| **2009** | 4 | 3,165,000 | 4,350,000 | 1,185,000 | 37 |
| | 5 | 2,145,000 | 4,325,000 | 2,180,000 | 102 |
| | 6 | 3,174,953 | 4,286,350 | 1,111,397 | 35 |
| | 7 | 2,750,000 | 5,850,000 | 3,100,000 | 113 |
| | 8 | 2,700,850 | 5,121,000 | 2,420,150 | 90 |
| | 9 | 3,150,000 | 6,265,000 | 3,115,000 | 99 |
| | 10 | 2,766,000 | 5,223,000 | 2,457,000 | 89 |
| | 11 | 2,510,000 | 6,371,000 | 3,861,000 | 154 |

Source: 2011 Survey

### 1.4.4 MONETARY ENTROPY FOR EARLY AND LATE CONSTRUCTIBLE ELEMENTS OF SAMPLED RESIDENTIAL BUILDINGS

Two (2) and three (3) bedroom bungalow bill of quantity was used in this context, divided into late and early constructible elements. Cumulative effect of cost influence factor and attendant risk often exerts pressure on projects monetary distribution. This concept is described as monetary entropy. Monetary entropy was defined by Cristodolou (2008) as inverse of variable probability. Entropy distribution of thirteen (13) projects of 2 &3-bedroom bungalow and s scheduled in Tables 1.4 and 1.5.

**Table 1.5 Projects Particular 2&3-Bedroom Bungalow**

| S/N | Element | Tender Cost[₦] | Tagged Project Cost[₦] | Relative Percent | Relative Probability | Relative Entropy |
|---|---|---|---|---|---|---|
| ELT1 | Substructure | 2,669,340 | 11,674,519.50 | 22.865 | 0.23 | 2.34 |
| ELT2 | Frame & Walls | 1,519,415 | 11,674,519.50 | 13.015 | 0.08 | 2.49 |
| ELT3 | Roofs | 1,197,000 | 11,674,519.50 | 10.253 | 0.10 | 2.47 |
| ELT4 | Window | 517,650 | 11,674,519.50 | 4.434 | 0.23 | 2.34 |

| | | | | | | |
|---|---|---|---|---|---|---|
| | s | | | | | |
| **ELT5** | Doors | 544,500 | 11,674,519.50 | 4.664 | 0.05 | 2.52 |
| **ELT6** | Finishing | 2,541,535 | 11,674,519.50 | 21.770 | 0.05 | 2.52 |
| **ELT7** | Fittings | 298,800 | 11,674,519.50 | 2.560 | 0.39 | 2.18 |
| **ELT8** | Services | 786,350 | 11,674,519.50 | 6.736 | 0.15 | 2.42 |
| **ELT10** | Soil Drainage | 274,000 | 11,674,519.50 | 2.347 | 0.43 | 2.14 |
| **ELT11** | Preliminaries | 500,000 | 11,674,519.50 | 4.283 | 0.24 | 2.33 |
| **ELT12** | Contingencies | 270,000 | 11,674,519.50 | 2.313 | 0.43 | 2.14 |
| **ELT13** | Value Added Tax (5%) | 555,929.50 | 11,674,519.50 | 4.762 | 0.21 | 2.37 |

Source: 2011 Survey

Samples of 2 & 3 bedroom bungalow project were analyzed based on cost centres; relative probability and entropy were quantified for each cost centres. Doors and Finishing work have highest entropy value of 2.52 followed by Frame and walls of 2.49 while Roofs has 2.0. The reason for high cost value of doors and finishings could be responsible for seasonal nature of the material supply and doors items that are often imported. Items with lowest entropy are soil and drainage including contingencies.

**1.4.5 Stabilizing Cost Centers for an Optimum Cost Using Neural Network.**

The training data set (300 samples) of 400 residential building projects selected, having being modified with inflation index and exigency factor, was used to train the multilayered perceptron neural network selected, so as to select its parameters, the one suitable to problem at hand. Back propagation was used to train the network since it is recommended and simple to code. So also gradient descent momentum and learning rate parameters was set at the start of the training cycle (for speed determination and network stability, range of momentum $0.1 \leq x \leq 1$, high = weight oscillation coefficient). The output is presented in Table 1.6.

**Table 1.6 Project Cost and Corresponding Neural Network Based-Entropy 2&3-Bedroom Bungalow**

| Project | Tender Cost | Tagged Cost | Neural Output | Relative Entropy |
|---|---|---|---|---|
| Prj 1 | 3085100 | 4236000 | 5,272,837 | 0.60 |
| Prj 2 | 3171800 | 5800000 | 7,219,654 | 0.44 |
| Prj 3 | 2610000 | 4800000 | 5,974,886 | 0.44 |

| | | | | |
|---|---|---|---|---|
| **Prj 4** | 3165000 | 4350000 | 5,535,606 | 0.57 |
| [redacted] | | | | |
| **Prj 6** | 3174953 | 4286350 | 5,454,607 | 0.59 |
| [redacted] | | | | |
| **Prj8** | 2700850 | 5121000 | 6,516,743 | 0.42 |
| [redacted] | | | | |
| **Prj10** | 2766000 | 5223000 | 6,669,763 | 0.42 |
| **Prj11** | 2510000 | 6371000 | 8,107,435 | 0.31 |
| **Prj12** | 3268000 | 6250000 | 7,953,456 | 0.41 |
| **Prj13** | 2,250,325 | 5675000 | 7,177,588 | 0.32 |
| **Prj14** | 3520000 | 6600000 | 8,347,503 | 0.42 |
| **P rj15** | 2100000 | 5125000 | 6,481,963 | 0.32 |
| **Prj15** | 3173000 | 5652000 | 7,148,498 | 0.45 |
| **Prj16** | 3173000 | 7650000 | 9,675,515 | 0.34 |
| **Prj17** | 2580315 | 6131000 | 7,754,324 | 0.33 |
| **Prj18** | 2420500 | 5643000 | 7,112,028 | 0.34 |
| **Prj19** | 3143000 | 7266000 | 9,173,691 | 0.34 |

Source: 2011 Survey.

Cost of four hundred selected residential building projects initiated and completed within 2009 and 2011 and processed with artificial neural network is presented in Table 1.6. The tender cost and as-built cost of the projects were adjusted with economic variants such as inflation index and exigency escalator buffer. The inflation index data of period of six month was factored into the as-built cost of the project. The modification will enable adequate coverage of intervening variables that impact cost and ensures continual validity of the developed model whenever deployed. The modified costs were loaded on back propagation neural network with Leven-berg Marqua and multilayer of input and output. The cost inputs were trained over 1000 training epoch and stopped when consistent output was produced to avoid technical dogmatism.

The outcome of network trained optimized cost is presented in Table 1.5. However, average sum of the neural network generated output was factored differentially into the elemental components of each project category and used as sample for the econometric based model.

The loading result of the elemental cost, loaded onto the three types of bid-balancing loading system, revealed that the econometric-modified system presented in this study, yields the best output in term sequential difference. There tends to be a close margin between the Econometric-Neural-based generated model cost output and tender sum used for the award of the projects. The implication of this discovery is that the model presents the Net Present Value (NPV) of the elements in an upward manner (futuristic) in terms of period 'n' in consideration. The model is used in achieving this feat. Therefore in determining the worth of an element at a period 'n', the project could be factored through incorporating inflation index, exigency escalator and inflation buffer. The neural network context was used to generate a consistent pattern of cost; the optimized cost is accepted as the generalized cost using desired modified econometric parameters as demonstrated in this study.

### 1.5 THE PROPOSED NEURAL NETWORK ECONOMETRIC UTILITY PARAMETER-BASED MODEL FOR RESIDENTIAL BUILDING PROJECT COST MANAGEMENT.

The Neural network econometric model for residential building project cost management is presented in this section. Three techniques were used to determine cost benchmark for each of the component of project elements. The early constructible element- loading, late-constructible element loading and individual- rate loading. This towed the line of submissions of Cattel et al., (2008) of front end loading, back-end loading and individual loading.

#### 1.5.1 Structural Component of Neural Network Econometric and Utility Parameter Modified Back-End Loading Approach

The neural network and econometric-based model for residential building project cost management is presented in this section. Three techniques were used to determine cost benchmark for each of the component of project elements. The early constructible element-loading, late-constructible element loading and individual- rate loading. This towed the line of submissions of Rosen (1974); Akintoye, A. and Fitzgerald, E. (2000); Brown and Rose (1982); Bajari and Benkard (2004); and Cattel, Bowen and Kaka (2008) of front end loading, back-end loading and individual loading.

$$Pjec = [\Sigma (1-r)^{-n}] \; ([C\lambda_{nj} [\gamma_{nj}Exf - C^1)] [\gamma_{nj}Exf_j - C^1)]) + \lambda_{nj} [Q_j + Q_i][\gamma_{nj}Exf_j - C^1)])$$

where rj --- Monthly Discount rate ;
n --- Period in Consideration;
$C^1$--Actual Increase in Cost of Items;
$\lambda_{nj}$ --- Proportion of Elements;
$Q_j$; $Q_i$ ---- Bill Cost of Item i, j;
$\gamma_{nj}$ --- Adjustment for Cost Escalation(risk factor) ;
Exf----Exigency Factor( project entropy = 2.36) and $C^1$ ---- unit cost of project element
Pjec – Project Element Cost.

The modified model was applied on 2&3-bedroom projects, the output of the model compared alongside with other front-end and individual rate loading. It was discovered that the values of the modified -econometric model is consistent in structure, the detail is presented in Table 1.7, from the table, the modified models' output is closed to the bill of quantity sums, the model has incorporated escalator buffer and inflation factor over a period of 6 (six months), which makes the assigned cost to the elements on the bill to be valid for six (6) months. For instance, the cost of substructure on the bill of quantities is ₦2,669,340 while after loaded with escalator buffer and inflation factor, ₦ 2939503.9. Once there is no incidence of inflation, contractor or builder will tend to save cost from onset while no effect of inflation will be felt on occasion of inflation during the course of the work execution. The econometric model output can then be used as tender sum for the elements at tender stage, since effect of project variants has been taken into consideration.

## 1.6 VALIDATING THE PROPOSED NEURAL NETWORK ECONOMETRIC UTILITY PARAMETER-BASED MODEL FOR RESIDENTIAL BUILDING PROJECT COST MANAGEMENT USING COMPARATIVE ANALYSIS OF THE ECONOMETRIC LOADING ATTRIBUTES

There is strong positive relationship between cost limit of 1-bedroom duplex and 2/3-bedroom bungalow with Pearson coefficient of 0.905, also there is very weak relationship with Pearsons correlation -coefficient of 0.45 that exist between the cost limit of 3-bedroom on four floors and 1-bedroom bungalow. However, from Table 1.7 averagely strong relationship is recorded as well in mapping 2/3- bedroom duplex with 4- bedroom duplex the analysis came up with Pearsons correlation coefficient of 0.787. Similarly, an average strong relationship occurred between 1-bedroom bungalow and 4-bedroom duplex; 3 bedroom on 4-floors and 2/3-bedroom bungalow with Pearsons coefficient of 0.764 and 0.586 respectively. Econometric value analysis of the three different methods is presented in Tables 1.7 and 1.8; there is weak correlation in the Individual-rate loading and Back-end loading when mapped with Front-end loading while positive correlation exists in mapping of Individual rate loading with Back-end loading this indicates closeness in the attribute as a result of incorporation of inflation buffer in the structure of the two models. However, the Econometric Back-end loading contingency coefficient from Table 1.8 is high with 0.967 and Kendall's tau coefficient of 1.00 at 99% confidence interval using Monte Carlo technique and closely followed by Individual-rate loading contingency coefficient of 0.957 and Kendall's coefficient of 0.909. This indicates better output as obtained from the generated econometric model whose weights are neural network modified.

## 1.7 ECONOMETRIC FACTOR ADJUSTED PROJECT ELEMENTS (2&3-BEDROOM BUNGALOW)

**Table 1.7 Econometric Factor Adjusted-Project Elements (2&3-Bedroom Bungalow).**

| | Element | Tender Cost[₦] | Tagged Project Cost[₦] | Front-end Loading | Individual -rate loading | Back-end Loading |
|---|---|---|---|---|---|---|
| R | | | | | | |
| ELT1 | Substructure | 2,669,340 | 11,674,519.50 | 3,012,567.00 | 737,298.40 | 2,939,503.90 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **ELT2** | Frame & Walls | 1,519,415 | 11,674,519.50 | 3,397,217.00 | 419,672.62 | 1,673,190.00 |
| **ELT3** | Roofs | 1,197,000 | 11,674,519.50 | 3,505,064.80 | 987,525.00 | 1,318,148.40 |
| **ELT4** | Windows | 517,650 | 11,674,519.50 | 3,735,654.40 | 142,980.11 | 570,041.41 |
| **ELT5** | Doors | 544,500 | 11,674,519.50 | 3,726,665.30 | 150,396.40 | 599,609.10 |
| **ELT6** | Finishing | 2,541,535 | 11,674,519.50 | 3,058,058.00 | 701,997.38 | 2,798,763.80 |
| **ELT7** | Fittings | 298,800 | 11,674,519.50 | 3,8018,925.70 | 82,531.60 | 329,041.60 |
| **ELT8** | Services | 786,350 | 11,674,519.50 | 312,645,694.00 | 217,198.00 | 865,936.80 |
| **ELT10** | Soil Drainage | 274,000 | 11,674,519.50 | 3,817,228.70 | 75,681.54 | 301,731.54 |
| **ELT11** | Preliminaries | 500,000 | 11,674,519.50 | 3,741,563.90 | 138,105.00 | 550,605.00 |
| **ELT12** | Contingencies | 270,000 | 11,674,519.50 | 3,818,567.90 | 74,576.7.00 | 297,326.70 |
| **ELT13** | Value Added Tax (5%) | 555,929.50 | 11,674,519.50 | 3,722,838.70 | 153,553.30 | 612,195.20 |

Source: 2011 Survey

**Table 1.8 Cost Limit Component Validations**

| **Elements and Parameters** | **Statistical** | **4-bedroomduplex** | **2/3-bdrmbunglw** | **1-bdrm bung** | **3-bdrm,3-floors** |
|---|---|---|---|---|---|
| **4-bedrmdplx Corr.** | **Pearsons** | 1.00 | - | - | - |
| | **Sig.(2-tailed)** | 0.00 | - | - | - |
| **2/3-bedrmbung Corr.** | **Pearsons** | 0.787 | 1.00 | - | - |
| | **Sig.(2-Tailed)** | 0.001 | 0.000 | - | - |
| **1-bedrm bunglw Corr.** | **Pearsons** | 0.764 | 0.905 | 1.000 | - |
| **Tailed)** | **Sig.(2-** | 0.001 | 0.000 | 0.000 | - |

**Table 1.9 Econometric Loading Attributes**

| Monte Carlo Technique | | Value | Asymp. Std. Error[b] | Approx. Sig. | Sig. | Lower Boundary |
|---|---|---|---|---|---|---|

| | | | | | | |
|---|---|---|---|---|---|---|
| 99% Confidence Interval | | | | | | |
| Individual-rate Loading | Contingency Coefficient | .957 | .233 | 1.000 | 1.000[a] | 1.000 |
| | Kendall's tau-c | .909 | .000 | .000 | .000[a] | .000 |
| Econometric Front-end Loading Coefficient | Contingency | -.95 | .233 | 1.000 | 1.000[a] | 1.000 |
| | Kendall's tau-c | -1.00 | | .000 | .000[a] | .000 |
| Econometric Back-end Loading Coefficient | Contingency | -.967 | .233 | .233 | 1.000[a] | 1.000 |
| | Kendall's tau-c | 1.00 | | | .000[a] | .000 |

Source: 2011 Survey

**CONCLUSIONS:**

The aim of the study is achieved, this study has developed an econometric model that incorporates neural network generated parameters, builders and contractors can therefore use the econometric-neural network based model in determining the magnitude of the cost implication of the elements to be able to prepare and submit a valid bid at procurement stage of building project. The model describes different dichotomies obtainable in a typical bill of quantities vis-à-vis early constructible element and late constructible elements. Sub-structural elements up to initializing elements of superstructure are regarded as early constructible elements while those billed to be executed later as project progresses are termed late constructible elements. Gleaning facts from data analyzed Sub-structural works which are often scheduled to be executed early on project carries high cost N2,939,503 followed by Frame and Roofs with N1,673,190 and N1,318,148 respectively. A builder can bill the component with their actual cost having being guaranteed of early released of fund for project execution. Meanwhile, elemental works often scheduled to come later on the project for execution should not be treated in this way, however there should be an anticipated cost loading on their elemental cost to cushion the effect of occurrence of uncertainties that may arise before execution, therefore model that incorporates an economic index will be most desirable for good effect. Econometric model like the one generated in this study will therefore accommodate factoring of upward lading time dependent factors on the elements. This takes account of present value of the cost using period 'n' in consideration as a base for reference, for instance, services and soil drainage that are often billed to occur later on project, which has tender cost of N786, 350 has a relative cost of N865, 938.80 produced by econometric model having being factored upward for period of six (6) months. Speculated period was used in context of this analysis, this will therefore provide a builder an opportunity to load a cost implication of unseen circumstance even if the money would be reimbursed later. This fact thus situates the neural network modified model as a tool that could be used in cost prediction over a specified period.

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