DATA ON EXPERT SYSTEM-ECONOMETRIC ENTROPY INFORMATICS MODEL FOR ADJUDICATING RESIDENTIAL BUILDING PROJECT COSTS

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Title: DATA ON EXPERT SYSTEM AND ECONOMETRIC ENTROPY-BASED INFORMATICS MODEL FOR ADJUDICATING RESIDENTIAL BUILDING PROJECT COSTS

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Abstract: This data article presents an expert system and econometric entropy-based informatics model for residential building project for cost judgment and decisions in residential building project. The data was obtained using Random sampling technique to select projects 1000 (one thousand) completed between 2009 and 2011, the project were examined for their cost centres. Also, As-built cost of (1000) one thousand projects were further selected and modified with econometric factors like inflation index, cost entropy and entropy factor to stabilized the data and were used to form and train neural network used. Probability technique was used to generate risk impact matrix and influence of entropy on the cost centres. A parametric model similar to hedonic models was generated using the utility parameters within the early and late elemental dichotomy. The model was validated through comparative analysis of the econometric loading attributes using Monte Carlo technique of SPSS software extracting the contingency coefficient. The data of the model can provide solution to the problems of knowing the cost implication of a future project and also enable a builder or contactor load cost implication of an unseen circumstance even on occasion of deferred cost reimbursement.

Keywords: Econometrics, Entropy, Adjudication Cost.

Abstract

This data article presents an expert system and econometric entropy-based informatics model for residential building project for cost judgment and decisions in residential building project. The data was obtained using purposive sampling technique to select projects completed between 2009 and 2011in Lagos state Nigeria, the project were examined for their cost centres. Also, As-built cost of one thousand(1000) samples of trained As-built cost of residential building projects trained with Neural network with Levenberg Marqua after being adjusted and modified with econometric factors like inflation index, cost entropy and entropy factor to stabilized the data and were used to form and train neural network used. Probability technique was used to generate risk impact matrix and influence of entropy on the cost centres. A parametric model similar to hedonic models was generated using the utility parameters within the early and late elemental dichotomy. The model was validated through comparative analysis of the econometric loading attributes using Monte Carlo technique of SPSS software extracting the contingency coefficient. The data of the model can provide solution to the problems of knowing the cost implication of a future project and also enable a builder or contactor load cost implication of an unseen circumstance even on occasion of deferred cost reimbursement.

Key words: Questionnaire, Utility parameters, Likert scale, Cost entropy, Adjudication.

Specifications Table

Subject area	***Building Construction; Construction Management.***
More specific subject area	*Artificial Intelligence Application*
Type of data	*Table, text file.*
How data was acquired	*Survey, Artificial Neural Network [Neuro Tools]*
Data format	*Raw.*
Experimental factors	**a.Data Training**: The training data set (1000 samples) of residential building 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.
Experimental features	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). 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]]]* $\diagup n$ **b. The testing phase**: Data from remaining 1000 samples were used as testing data set to produce output for unseen sets of data. A spread sheet 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]] $\times$ 100% MEE = [$1/_n$][[I = n]. summation over (i = 1)] cpe(i)
Data source location	*The data was sourced from Construction Firms in Lagos state and Bureau of Statistics Abuja Nigeria, Nigeria.*
Data accessibility	*Data is with the article.*

Value of the

1. The data would be useful in assisting builders, engineers and all categories of site practitioners in using econometric models to determine magnitude of cost implications on construction sites.
2. The data could enable client and tenderers to decide correctly on site cost issues.
3. The data provides platform for further research in Application of Artificial Intelligence in solving construction problems.
4. It provides basis for literary and practical contribution in the field of construction economics research.

Data

The data being presented includes: Factoring Elemental Cost Centers Influence on Project Cost, Entropy Level and Risk Threshold Perspective on Project Cost, Cost and Risk Impact Prediction Probability Matrix, Cost monetary Entropy Summary of Adjusted Projects B.O.Q Value and As-built Cost of 4-Bedroom Duplex, Cost Schedule for 2-Bedroom Bungalow, Early And Late Constructible Elements Monetary Entropy for Sampled Residential Buildings, Project Cost and Corresponding Neural Network Based-Entropy 2&3-Bedroom Bungalow, Structural Component of Neural Network Econometric Modified Back-End Loading Approach, Comparative Analysis of The Econometric Loading Attributes of Neural-Network Econometric Entropy-Based Model , Cost Limit Component Validations, Econometric Loading Attribute

1.1.1 Experimental Design, Materials and Methods

The Training Stage: The training data set One thousand (1000) samples of residential building projects were modified with inflation index and exigency factor. It was used to train the multilayered perceptron neural network with Levenber Marqua selected, so as to select its parameters, the one suitable to problem at hand.

[1-6]. 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[6-9].

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[10-12].

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

b. The testing phase: Data from 1000 samples were used as testing data set to produce output for unseen sets of data. A spread sheet 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]] $\times$ 100% ------(2)

MEE = [$1/n$][[I = n]. summation over (i = 1)] cpe(i)-----(3)

Table 1.1: Factoring Elemental Cost Centres Influence on Project Cost

S/N	**Elements**	**Cost Rating On Scale Probability(P=0.0 to 1.0)**			
C.		4-Bedroom Duplex	2/3- Bedroom Bungalow	1- Bedroom Apartment	3&4- Bedroom, 4 Floors
ELT1	Substructure	1.0	1.0	1.0	0.8
ELT2	Frame & Walls	1.0	1.0	1.0	1.0
ELT3	Stair Cases	0.2	---	---	0.3
ELT4	Upper Floor	0.9	---	---	0.4
ELT5	Roofs	0.7	1.0	1.0	0.4
ELT6	Windows	0.5	0.4	0.5	0.5
ELT7	Doors	0.6	0.5	0.5	0.5
ELT8	Finishing	1.0	1.0	1.0	0.1
ELT10	Fittings	0.2	0.3	---	0.6
ELT11	Services	0.7	0.7	0.6	0.7
ELT12	Soil Drainage	0.2	0.2	0.7	0.6
ELT13	Preliminaries	0.4	0.4	0.5	0.7
ELT14	Contingencies	0.3	0.2	0.3	0.3
ELT15	Value Added Tax (5%)	0.5	0.5	0.5	0.1

Source: 2011 Survey

The data presented in the table above is on ordinal scale of 0to 1. 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

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).

Table 1. 2: Data of Probability Matrix for Predicting Projects Cost and Risk Impact [Probability Scale of 0.0 to 1.0]

PROBABILITY	4 -bedroom Duplex	2&3-bedroom Bungalow	1-bedroom Apartment	3 /4-bedroom, 24 Units 4 Floors
EXTREME 0.7-1.0	1.0Substruct. 1.0Finish 1.0Frame 0.7Service 0.9Uppfloor 0.7Roof	1.0Substructure 1.0Frame 1.0Roof 1.0Finishing	1.0 Finishing 1.0 Substructure 1.0 Frame ------ ------- 1.0Roof	1.0 Frame 1.0Finishing
HIGH 0.6-0.8	0.5Window 0.6 Doors	0.7Services	0.6Services 0.7Soildrainage	0.8Substructure 0.6Fittings 0.6Soildrainage 0.7 Services 0.7 Services
MEDIUM 0.3-0.5	0.3Contigenc 0.4Preliminar 0.3 Contingency	0.3 Fittings 0.5 VAT 0.4 Wind 0.5 Doors 0.4 Prelim	0.5 Window 0.5 Prelim 0.3 Doors 0.5 Soildrainage 0.5 VAT	0.3 Stairсs 0.4 Upperfloor 0.4 Upperfloor 0.5 Windw 0.5 Doors 0.3 Contingency

LOW 0.0-0.2	0.2 Stair 0.2 Soildrain 0.2 Fittings	0.2SoilDrainage 0.2Conting		
	1	2	3	4

IMPACT/CONSEQUENCE

The data presented in the table above is ordinal in nature. Data in table 1.2 above contain comparative analysis of risk elements of 4–bedroom duplex, 2&3-bedroom Bungalow, 1-bedroom Apartment, 3 /4-bedroom, 24 Units 4 Floors risk elements with risk implication on the project. The following elements have high risk implications on Residential building Duplex and Bungalow: Substructure, Finishing, Frame, Service, Upper floor and Roof. More attention on those elements would help prevent financial wastage and in balancing of cost at tendering stage. Also the contents with high risk impact in Residential buildings with more floors include Frame and Finishing

1.4.3 Evaluating Project Cost Monetary Entropy

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 Variation	Percentage Entropy
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

Data of cost distribution pattern was presented in the analysis presented in Table 1.2 and 1.3. The data presented is categorical in nature. 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 magnitude of the entropy.

1.4.4 Early and Late Constructible Elements Monetary Entropy for Sampled Residential Buildings

Table 1.5 Projects Particular 2&3-Bedroom Bungalow

S/N	Element	Tender Cost[₦]	Tagged Project Cost[₦]	Relative Percent	Relative Probability	Relative Entropy
B.						
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	Windows	517,650	11,674,519.50	4.434	0.23	2.34
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

This data presented above can help in determining the rate at which cost of each elements could vary relative to elements of a project. The data indicated that Doors and finishing cost has the most frequent fluctuation, followed with frame and windows. The cost of those elements need to be properly taken into consideration in order not to delay work or affect entire project negatively. The cost entropy presented in the table could help contractors to achieve the purpose.

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

The training data set (1000 samples) of residential building projects were 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 [8-13].

Table 1.6 Data on Training of Project Cost of 2&3-Bedroom Bungalow with Neural Network

Project	Tender Cost(N)	Tagged Cost(N)	Neural Output(N)	Relative Entropy
Prj 1	3085100	4236000	7,3672,737	0.70
Prj 2	3171800	5800000	7,345,657	0.84
Prj 3	2610000	4800000	6,794,688	0.64
Prj 4	3165000	4350000	6,635,806	0.39
Prj 5	2145000	4325000	6,855,924	0.87
Prj 6	3174953	4286350	6,654,957	0.69
Prj7	2750000	5850000	6,592,822	0.67
Prj8	2700850	5121000	6,516,743	0.42
Prj9	3150000	6265000	6,872,945	0.50
Prj10	2766000	5223000	6,669,763	0.42
Prj11	2510000	6371000	6,587,965	0.61
Prj12	3268000	6250000	6,983,746	0.51
Prj13	2,250,325	5675000	6,857,236	0.42
Prj14	3520000	6600000	6,837,329	0.52
P rj15	2100000	5125000	6,787,856	0.43
Prj15	3173000	5652000	6,348,498	0.45
Prj16	3173000	7650000	6,575,585	0.44
Prj17	2580315	6131000	6,257,278	0.43
Prj18	2420500	5643000	6,468,567	0.44
Prj19	3143000	7266000	6,634,734	0.46

Data of selected Nineteen (19) project samples of the 1000 building projects sample. Nineteen(19 Neural network trained samples which are found to be consisted in value were selected and presented in the table 1.6 above. The lowest cost indicated in the data above is for lowest cost generated through neural network training of the data trained by the neural network; the cost is N6,635,806 with corresponding cost entropy of 0.39.The highest cost entropy generated is 0.87 with cost of N6,855,929. The cost data range therefore that could be chosen as As-built cost of 2-3 bedroom bungalows. To predict future cost of construction cost,entropy presented could be factored into any cost to predict the future value. The data found utility in developing hedonic model such as presented in section 1.5.1

1.5 Data of the Expert System And Econometric Entropy-Based Model For Residential Building Project Cost Adjudication.

The expert system and econometric entropy-based model for residential building project cost adjudication 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 [12-15].

1.5.1 Data on Structural Equation of Developed Neural Network Econometric Modified Back-End Loading Model

A structural hedonic equation was previously developed, which could be used to generate data for adjudication of various project elements and problem of cost implication determination. The probability matrix of tables 1.1, 1.2, 1.3 and 1.4 was used to generate data presented in section 1.6.

Developed Neural Network Econometric Modified Back-End Loading Model = $Pjec = [\Sigma (1\text{-}r)^{-n}]$ $([C\lambda_{nj} [\gamma_{nj} Exf - C^1)] + \lambda_{nj} [Q_j + Q_i][\gamma_{nj} Exf_j - C^1)])$

where rj --- Monthly Discount rate ;

n --- Period in Consideration; C^1--Actual Increase in Cost of Items; λ_{nj} --- Proportion of Elements;

Q_j; Q_i ---- Bill Cost of Item i, j; γ_{nj} --- Adjustment for Cost Escalation(risk factor) ; ----Exigency Factor(project entropy = 2.36) and C^1 ---- unit cost of project element ; Pjec – Project Element Cost.

1.6 Data on Validated Developed Neural Network Econometric Modified Back-End Loading Model Using Comparative Analysis Of The Econometric Loading Attributes

Table 1.7 Data on Structural Equation of Developed Neural Network Econometric Modified Back-End Loading Model using (2&3-Bedroom Bungalow).

	Element	Tender Cost[₦]	Tagged Project Cost[₦]	Front-end Loading	Individual-rate loading	Data treated with Developed Structural Equation
B.						
ELT1	Substructure	2,669,340	11,674,519.50	3,012,567.00	737,298.40	2,939,503.9
ELT2	Frame & Walls	1,519,415	11,674,519.50	3,397,217.00	419,672.62	1,673,190.0

ELT3	Roofs	1,197,000	11,674,519.50	3,505,064.80	987,525.00	1,318,148.4
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	2,798,763.8
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	312,645,694.0	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	74,576.7.0	297,326.70
ELT13	Value Added Tax (5%)	555,929.5	11,674,519.50	3,722,838.70	153,553.30	612,195.20

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 [13-15]. Brown and Rose (1982); Bajari and Benkard (2004); and Cattel, Bowen and Kaka (2008) of front end loading, back-end loading and individual loading. Data of treatment of the project data with the three loading models mentioned was used to generate comparable project cost for tendering purpose and other purpose.

The data would be much useful for purpose of tender reparation. Due attention should be given to the Substructure and Finishing since they emerged as the elements with high cost of execution successful allocation would guarantee 80% success of the project. The cost category developed with the data treated with developed structural equation showed stability than other two, therefore recommended for use in project cost prediction .i.e. data treated with developed structural equation

Table 1.8 Cost Limit Component Validations of the Developed Neural Network Econometric Modified Back-End Loading Model

Elements and Statistical Parameters		**4-bedroomduplex**	**2/3-bdrmbunglw**	**1-bdrm bung**	**3-bdrm,3-floors**
4-bedrmdplx	**Pearsons Corr.**	1.00	-	-	-
	Sig.(2-tailed)	0.00	-	-	-
2/3-bedrmbung	**Pearsons Corr.**	0.89	1.00	-	-
	Sig.(2-Tailed)	0.001	0.000	-	-
1-bedrm bunglw	**Pearsons Corr.**	0.886	0.895	1.000	-
	Sig.(2-Tailed)	0.001	0.000	0.000	-

Table 1.9 Econometric Loading Attributes Developed Neural Network Econometric Modified Back-End Loading Model

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	Contingency Coefficient	-.95	.233	1.000	1.000[a]	1.000
	Kendall's tau-c	-1.00		.000	.000[a]	.000
Econometric Back-end Loading	Contingency Coefficient	-.967	.233	.233	1.000[a]	1.000
	Kendall's tau-c	1.00			.000[a]	.000

Data of Re-sampling test was presented on the model in order to ascertain the stability and the influence of outliers on the models' stability. The data results are presented in Tables 1.8 and 1.9; two models are presented here, model of as-built sum and Econometric Front-end Loading and Individual-rate loading has standard error of 0.233. The two models can help in tender sum preparation to load cost implication of unseen variables that could help in tender sum prediction. The two models showed stability with high level of tolerance.

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