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Fwd: Acceptance of paper 384 for 22nd IBIMA Conference

2 messages

zahra Manager <zahra.ibima@gmail.com> Thu, Oct 10, 2013 at 3:24 AM
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Dear Dr. Amusan Lekan M, Dr. Ayo Charles K, Dr. Mosaku Timothy, Dr. Fagbenle Olabosipo, Dr. Tunji-Olayeni P, Dr. Owolabi James, Dr. Omuh Ignatius and Dr. Ogunde Ayodeji,

Congratulations! I am pleased to inform you that your paper submission “Neural Network-Ant Colony Optimization Model of Residential Building Project Cost: Exploratory Approach," to the International Business Information Management Conference (22nd IBIMA) on 13-14 November 2013 in Rome, Italy has been accepted for presentation at the conference. The paper will be included in the conference proceedings (ISBN:978-0-9860419-1-4) as a full paper.

The paper, after addressing review comments, is recommended for consideration for “Journal of African Research in Business & Technology" published by IBIMA publishing. Journals website: www.ibimapublishing.com

If you are interested in the journal publication as well, please include publication charges in the registration form.

Attached to this e-mail:

1) Camera ready format guidelines for 22nd 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)

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 25 October 2013. Make sure to follow the attached guidelines in preparing this document. Please be sure to include the reference #384 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 25 October 2013. However, in order for the presentation to be included in the conference and the proceedings, one author must register by 25 October 2013.

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,
Dr. Khalid S. Soliman
22nd IBIMA Conference Chair

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Amusan Lekan <lekan.amusan@covenantuniversity.edu.ng> Mon, Dec 30, 2013 at 4:37 PM
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Dr. Lekan Amusan Covenant University Nigeria.

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Neural Network-Ant Colony Optimization Model of Residential Building Project Cost: Exploratory Approach

Amusan Lekan M[1], Ayo Charles K[2], Mosaku Timothy[3], Fagbenle Olabosipo[4],Tunji-Olayeni P[5], Owolabi James, Omuh Ignatius[6] and Ogunde Ayodeji[7]

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Abstract

Neural network and ant-colony are two important tools that could be used to provide solution in situation of multivariate environment that requires pareto optima solutions. In this study therefore, combination of neural network and ant colony method was used to generate an optimization cost model. Neural network is a conventional method currently being used in cost modeling, given its advantage over traditional regression method. It is based on this, that this study used the combination of neural network and regression method to model cost of residential building projects. One hundred and fifty (150) samples of residential building projects were selected at random and divided into two; one part is used in developing network algorithm for neural network and ant colony, while the second part is used for model validation. Neural network is used to generate which was divided into modules: the data optimization module, criteria selection with initializing and terminating modules. Regression analysis was carried out and model validated with Jackknife re-sampling technique and previously developed ant colony model (MOACO, MOTACO and MAWA). The co-linearity analysis indicates 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. The model is flexible in accommodating new data and variables, thus, it allows for continuous updating.

Keywords: Expert system, Co-linearity, Informatics, Residential-Building.

1.1 Cost Modeling: Historical Perspective

Cost model in construction parlance model can be described as systematic arrangement of project cost center into cost packets for easy manipulation with aid of figures and symbols. Floor area method was discovered in early nineteenth century, while storey enclosure method was developed in 1954. (Skitmore 1990). However, storey enclosure method was discovered to be more accurate in cost estimating than cube and floor area methods (Skitmore 1990). Cost modeling technique using statistical techniques was evolved around mid 1970-1979, this includes the use of approximate quantity and optimized models. Validating the applicability of developed model was the order of the day, given the seemingly applicable nature of models generated, while the models were classified as hedonic model (Rosen 1974). However, Rosen (1974) laid the foundation for the application of model in hedonic form and application of regression-based models. Also, 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, this fact induced paradigm shift later shifted in the direction of application of expert system as Brandon (1987) advocated, the development favored expert system application such as neural network, neuro- fuzzy, ant colony among others. The development was aided by good attributes of expert system, given the expert system background of good characteristics such as capacity to accommodate large data input, consistent output, output and input mapping, consistent output, low variation error between input and output.

1.2 Perspectives in Application of Cost Model

Models in construction research can be broadly classified into two: the product-based and process based model. A school of thought classified model as product-based while other classified it as process-based. Ferry (1999), Moore, Lees and Fortunes (1999), defined product-based model as system that models finished form of a product or service. Process-based model on the other hand synthesizes a model through the modeling process of such model.

Similarly, Mawdesley (1997) and Asworth (1994) suggested elemental, regression, heuristics and expert system as some of approaches in modeling as 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, inflation change among others (Moore et al., 1999).

Moreover, Li et al., (2005) submitted 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.

Finally, 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 within the range of 2% to 4% while parametric model(regression model) often have variation error greater than 7%.

1.3 Concept of Ant Colony Optimization (ACO)

In recent years, several innovative approaches have been invented in the field of operations research, about the method that could be used in providing an optimum solution in situation of complex choice of better alternatives. In multi-conflicting objective situation, pareto optimal solution is often desirable, pareto optimal system combines meta-heuristic approach in solving combinatorial solutions, one of such pareto optima systems is ACO. Ant colony optimization was first proposed by Dorigo (1992) ACO illustrates how ant colonies work to provide solution to optimization problem. Ant colony simulates ant behavior while searching for food, they uses pheromone to communicate food location. Although ant behaves like a partially blinded being, yet they achieve much through synergy, once an ant locates a shortest route to a food source, it reinforces it with pheromone to make attractive to other ant to follow, they therefore trod the food path based on the amount of pheromone deposited on the path until the food is exhausted, the short path located is referred to as objective function (path) while the less trodden path becomes weaker due to disappearance of pheromone.

However, many researches have been devoted to ant colony optimization (ACO) techniques. ACO is described in Hlaing and Khine (2011) as a method used in allocating non-linear resources and was used to provide solution to travelling salesman's problem, Yin Peng-Yen and Wang (2006) described it as method that could be used in linear resource allocation to a limited number of resources over a given range of constraints. The study represents an application of ant colony optimization technique in resource allocation and algorithm developed was validated with worst-case analysis. In a related study, ACO was adopted in Hlaing and Khine (2011) to generate algorithm for solving travelling salesman problem, it is considered as one of the heuristic algorithm than can be applied in solving travelling salesman problem.

1.4 Research Methodology

The objective of this study is to generate an exploratory study of cost modeling of residential building projects in Nigeria. However, the following innovative approaches were introduced in this work; setting cost modeling historical background of hedonic models and regression models, modification of project cost with economic stimulants like inflation indices, training and stabilizing cost centers with artificial neural network and ant colony optimization of project costs, jackknife validation of developed model.

1.4.1 Data Source

In this study, One hundred and fifty (150) 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. 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. Ant colony method and Multi-Layer Perceptron Neural network with Back Propagation system and Levenberg Marqua was used as configuration frame work, and from Table 1.1 One thirty-six (136) of the samples was used in model testing, while fourteen (14) samples were used in model training for configuration of optimization algorithm. The method is in line with method used in sample selection of application of this nature, it includes those presented in submissions of Setyawati et al.,(2007), Choi and Russel (2005) and Seah (2005).

1.4.2 Analytical Process for Application of Neural Network and Ant Colony Method in 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.

1.4.3 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.

1.4.4 Data Description: This study used cost significance work package in breaking down the project cost to their constituent's components. It involves 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 being used.

1.4.5 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, 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.

1.4.6 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.

1.5 Research Methods and Analytical Process of Ant Colony Optimization System

Cost entropy of project elements were calculated and tabulated. Ant colony algorithm was developed for the processing of the data and contingency table developed for illustration of algorithm parameters. However, the algorithm deployment follows regular ACO pattern as suggested in Dorigo (1992); Bell and McMullen (2004) and Chahasooghi and Kermani (2008) in the following order: initialization of solution, heuristic identity formulation, pheromonal updating and reinforcement parameters, developing selection probability and defining termination parameters. The development of the algorithm and the analytical process was therefore formatted in the stated order.

1.5.1 Initialization of Problem Solution

The first task is problem definition for identifying an optimal solution. The major task here is finding an optimal solution to the challenge of allocating cost to project cost elements considering the upper and lower cost allocation limits. Finding an optimal solution sets grounds for determining project cost centers entropy state. However, cost entropy is probabilistic in nature; it was quantified in this study as an inverse of probability function of cost in consideration, it is represented by the following function: Ce = P-1, where Ce is cost entropy, and P is probability value for the optimized cost option for each project cost centers

1.5.2 Heuristic Identity Formulation.

ACO searches for optimum value of variables by iteratively evenly distributing an ant search agent(cost-entropy). The search agents is the cost entropy as it moves through the cost elements, at each of iterations, the cost-entropy(an imaginary ant) traverse the edge of the trail to generate solution which favors the path with high density of pheromones (Ying et al; 2006). The algorithm used in this context is presented in the following order:

Initialization of Cost and Entropy Function, Problems Graphical Representation Formulating Initializing Phenoromonal Constants, Repeat for each Ant on each cost centers, Proceed to next node based on Transition rule, Construct a Solution, Reinforce the

Pheromone based on Updating rule, Is updating Rule fulfilled? Yes? Stop; No? Revert to first step, and select the Optimized Solution.

1.5.3 Problem Formulation

This study utilized non-linear resource allocation strategy, by considering the problem as discrete in nature as advocated by Yin and Wang (2008). It adopted project cost center (Pc) with C units of the same type of discrete cost resource. The quantity of resource allocated to project cost centers 'i' is constructed in the limits (aij; bij). The cost attached on the project cost elements is regarded as a linear integer function which is premised on the task composition of the elements. The task is formulated as follows: J(x) = subject to $0 \leq ai \leq$ $\leq bi \leq$ Qi where is an integer and quantity of cost resource allocated to j, fi is the cost function, Q is project cost centers di is regarded as lower boundary of quantity of resource allocated to task i, while bi is the upper bound for quantity of resource allocated to task i.

1.5.4 Developing Multi-objective Ant Colony Optimized Model

Problem formulation often sets background for ACO model formulation. However there is a need to set working parameters for developing the model. Such parameters includes; pheromone quantity parameter at the edge 'i.j,' αi.j (initial number of cost options), amount of initial quantity of pheromone (x=1). Alpha (α) = PCo is the project cost options, when x takes values from 0 to 1. Rho (P) is the constant that represents vanishing rates of pheromone, the value can range from 0.49 to 0.99, the higher the value the stronger the reinforcement of the rail. Also, cost entropy value is denoted, by ηi.j= 1/di.j where di.j is the cost entropy of an ant kth tour, this refers to the cost of using a particular cost resource options in between activities. Alpha (α) and Beta (þ) values represents controlling parameters on selected cost entropy output. The higher the values of α1 the better the chances of cost centers with low cost magnitude being selected and vice versa, by the imaginary ant, which represents cost iteration arrowheads. This submission is premised on Dorigo (1992) assertion that, parameters α and þ concentrations determines the pattern of ants' path selection, therefore higher value of the two parameters would make the iterative path selected be more attractive, thus influences the concentration of pheromone. Parameters Alpha (α) and Beta (þ) were adjusted till β=0.01, while Alpha α= 1. ΛT is used to represent concentration of pheromone deposited during iterations. ΛT = 1/Li.j , where Li.j equals cost which is taken as function of time.

1.5.5 The Testing Phase: For Neural network modeling, thirty (30) samples of the remaining samples was used in model training.

1.5.6 Anaysis of the Developed Model

Stepwise regression analysis is 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 1.2.

Table 1.1 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

Table 1.2 Regression Coefficients of the Developed Model

			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: Data Analysis 2012 Note: Correlation is significant at the 0.01(2-tailed).

Table 1.3 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

Table 1.4 Coefficients Matrix of Residential 2-3 -Bedroom Buildings Project

Model		Unstandardized Coefficients		Standardized Coefficients			Collinearity Statistics	
		B	Std. Error	Beta	t	Significance	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

Correlation matrix in Tables 1.2 and 1.3 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 1.4 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.

1.5.7 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 1.4 and 1.5; 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.

1.5.8 Cross Validation Test on The Model

Table 1.5 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 1.5 and 1.6.

Table 1.6 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 1.7 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 1.8: Ant Colony Algorithm Contingency Schedule

Elements	Neural Modified Lower C.B	Neural Modified Upper C.B	Entropy	α_1	β_1	J(x)	$\beta(\eta_1)$
Substructure	29,958,952	30,000,000	0.015	1.000	0.010	41,048	66.670
Frame and Walls	41,899,114	42,000,000	0.015	1.000	0.010	100,886	66.670
Roofs	15,847,852	16,000,000	0.072	1.000	0.010	152,148	13.890
Windows	11,723,069	12,500,000	0.055	1.000	0.010	76,931	18.180
Doors	544,500	545,000	0.055	1.000	0.010	500,000	18.180
Finishings Works	2,541,535	2,600,000	0.015	1.000	0.010	58,465	64.940
Fittings	298,800	300,000	0.018	1.000	0.010	1,200	55.560
Services	786,350	800,000	0.025	1.000	0.010	13,650	40.000
Soil and Drainage	274,000	276,000	0.011	1.000	0.010	2,000	90.91
Preliminaries	500,000	550,000	0.045	1.000	0.010	50,000	20.41
Contingency	270,000	280,000	0.031	1.000	0.010	10,000	32.26
VAT	555,929	560,000	0.052	1.000	0.010	4,071	19.23

Legend: α_1,β_1: Controlling Parameters $\rho\eta_1$: Phenoromone Vanishing Function
J(x): Quantity of Allocated Cost Resource on Cost Center C.B: Cost Boundary

Table 1.9: Validating Framework for Ant-Colony Algorithm

Solution	Time	Cost	Model
1	61	173,300	50- MAWA
2	61	173,000	100-MAWA
3	61	173,000	30-MOACO
4	60	165,000	Lakshiminarayana MOTACO
5	53	152,148	MOCEACO

1.5.9 Analysis of Results and Discussions

Results analysis and discussions are presented in this section. Neural network modified cost of the building project was optimized for the arrow head of imaginary ant-like travelling cost, which creates interesting cost path along the project cost centers. Minimum of ten (10) projects were selected for analysis, the costs were analyzed for their elemental cost component after which average sum of the elements was estimated and processed for their pheromone concentration. In Tables 1.8 and 1.9, details of Ant Colony Optimization (ACO) contingency schedule is presented, illustrating upper and lower boundaries of the cost elements. ACO algorithm parameters were simulated in the contingency schedule. The parameters include: controlling parameters β and α (the initial number of cost options), which are set at 0.01 and 1 respectively, ρ (rho) is regarded as pheromone vanishing constants, $\eta i.j = 1/ di,j$ which represents cost entropy of ant Kth tour. In following shortest route, while J(x) which is equivalent to represents quantity of allocated cost to the elements. Entropy is the inverse of the cost centers probability. From Tables 1.8 and 1.9, highest entropy value occurred on Roofs with J(x) value allocation of ₦152,148 with least on Soil and drainage.

A trend emerged in the analysis, element with low entropy values tend to have higher ρ (rho) value, that is, pheromone trail, this indicates that the path of accomplishing this task will be favorable to the imaginary ant 'k' which sought the tasks in order to complete them. Elements such as Substructures, Frame and Walls, Finishing, Soil and drainage work has high pheromone concentration, this attracts attention of ants to them thus shortest routes are created to them and are executed quickly, simulating these activities on a network indicates level of their criticality, therefore have no float. The successful execution of these tasks would guarantee 80% completion of the whole tasks. Those elements with lowest concentration of pheromone are less attractive, thus could be combined with those of high concentration for total completion of the project tasks.

Table 1.9 presents validating framework for Ant Colony optimization algorithm (ACO) developed, in the study carried out by Zheng et al; (2005) MAWA and MOACO were developed with an optimized cost of $173,000 and processing time of 60 seconds. Likewise, the MOACO model developed by Lakshiminarayana et al; (2010) has optimized cost of $165,000. The optimized cost ₦152,148 was generated in this study through the cost entropy multi-parameters Ant Colony Optimization (CEMACO) algorithm with 53 seconds processing time. This is somehow lower than values of previous models.

A neuro-ant colony cost optimization 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 includes; 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).

The objective of the research work is achieved; the exploration of the technical essence of artificial neural network and ant colony optimization in developing a workable algorithm for solving cost problem in building work as presented in this study. The model developed is capable of assisting builders at loading implications of unseen variables that influences project cost in construction work and then plan against them, it is useful at all stages of building projects.

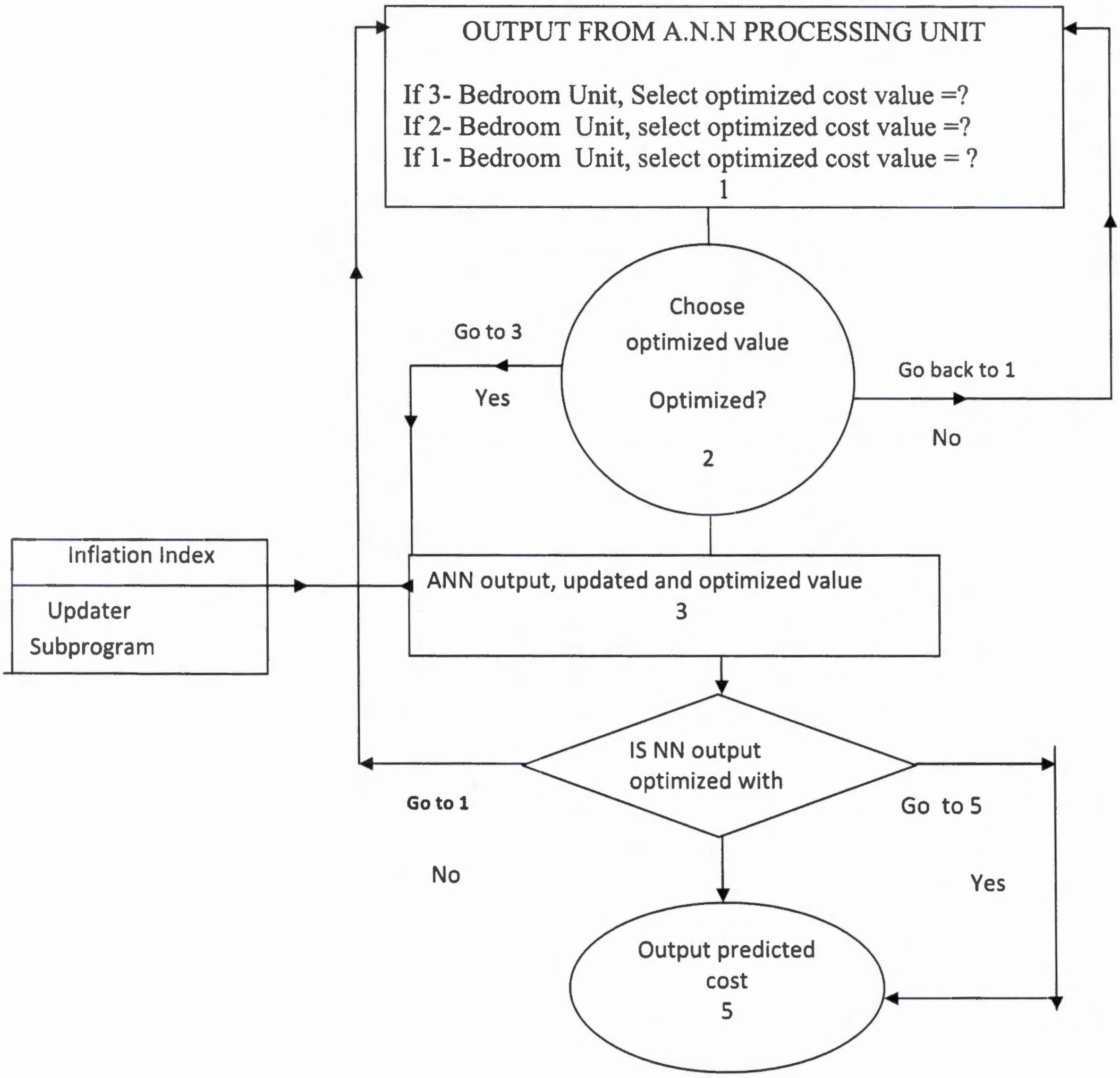

Fig. 1: Building Cost Variable Optimization Algorithm (Flow Chart)

Reference

Ashworth, A (1994) Cost studies of Buildings, Third Edition. Longman Scientific and Technical. New Yorks.

Brandon, A. (1987) Cost modeling for Estimating. The Royal Institution of Chartered Surveyors.

Bell and McMullen (2004) Ant Colony Optimization Techniques for the Vehicle Routing Problem. *Advanced Engineering Informatics.*18, 41-48.

Cattel,W.D., Bowen,P.A., and Kaka, A.P. (2008). A Simplified Unbalanced Bidding Model. *Construction Management and Economics.* 26(10-12), 1291-1302.

Chahazooghi, S.K and Kemani, A.H.M. (2008) An Effective Ant Colony Optimization Algorithm (ACO) for Multi Objective Resource Allocation Problem. *Applied Mathematics and Computing.* 200,167-177.

Choi, J. and Russell, J.S. (2005) Long-term Entropy and Profitability Change of United States Public Construction Firms. *Journal of Management in Engineering,* 21, 17-26.

Christidolou, S. A. (2008 September) Resource-Constrained Scheduling Using Ant Colony Optimization. Paper presented at the Ninth International Conference on the Application of artificial Intelligence to Civil, Structural and Environmental Engineering. St.Julian,Malta.

David, P and Seah, M (2004). Implementation Issues in Neural Networks Development. *Neurovest Journal.* United States of America: Idea Group Incorporated. 10 (7). Nov/Dec, PP 8-12.

Dissanayaka, S.M and Kumaraswamy, M.M (2007) Comparing Contributory Time and Cost Performance in Building Projects. *Building and Environment.*31 (6), PP 569-578.

Dorigo, M. (1992). "Optimization, Learning and Natural Algorithms."Ph.D Thesis, Dipartimento di Elettronica, Politecnico di Milano, Italy.

Gwang-Hee K, Sang-Hoon A and Kyung-ink, (2004). Comparison of Construction Cost Estimating Models Based on Regression Analysis, Neural Networks, and Case-Based Reasoning. *Journal of Building and Environment.* 39, PP1235 – 1242.

Hlaing, Z.S.S and Khine M (2011) Ant Colony Optimization Algorithm for Solving Travelling Salesman Problem. Proceeding of International Conference on Information Communication and Management. IPCSIT. 16.54-59.

Lakshiminarayana S; Guarav A and Arun C (2010) Multi-objective Optimization of Time-Cost-Risk Using Ant Colony Optimization. *International Journal of Project Planning and Finance.* 1(1). 22-38.

Li Heng, Shen Q.P and Love Peter (2005). Cost Modeling of Office Building in Hong Kong: An exploratory study." *Facilities.* United Kingdom: Taylor and Francis. 23(9/120), PP 438-452.

Mawdesley, M.J; Williams, A and O'Reilly M (1999). Planning and Controlling Construction Project. Addison Wesley Longman. Harlow, England.

McKim, R (2005a) Neural Network Application to Cost Engineering. Cost Engineering. *AACB International.* Vol. 35 (7), Pp 31-35.

Moore C.F; Lees, T. and Fortunes, C (1999) The Relative Performance of Traditional and New Cost Models in strategic Advice for Clients. *RICS Paper Series.* London: Prentice Hall Publishers. PP 45-57.

Rosen H.S (1974) Hedonic Prices and Implicit markets: Product Differentiation in Price Competition. Journal of Political Economy, 82.

Setyawati, B. R, Sahirman S and Creese R. C, (2007). Neural Networks for Cost Estimation. *ASCE International Transactions;* 13(9) PP 22

Skitmore, R.M, and Ng, S.T.(2003) Forecast Models for Actual Construction Time and Cost", *Building and Environment.* 38(8), Pp 1075.

Thawornwong, S and Enke, D (2004). Forecasting Stock Returns with Artificial Neural Networks. *Intelligent Engineering Systems through Artificial Neural Networks.* 12, PP 695-705.

Ying Peng-Yen and Wang Ying-Yu (2006) Ant Colony Optimization Algorithm for the Non-linear Resource Allocation problem. Apply mathematics and Computing.174.1438-1454.