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Multi-Parameter Optimization of Cost Entropy for Reinforced Concrete Office Building Projects using Ant Colony Optimization

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Abstract: Ant colony optimization is one of the conventional techniques used in providing solution to multi-objective optimization situations where pareto optimal solution is desirable. The main aim of this research work is to develop an optimization system for cost-entropy optimization logic and this study has demonstrated succinctly the applicability of ant colony optimization algorithm in solving multi-conflicting objectives situation in cost entropy trade-off of reinforced concrete office building projects. Average costs of (14) elements of (20) selected projects were used for the analysis. The ant colony system devised was applied on 14 in 20 elements of the sampled projects. An optimal solution obtained was validated within the context of previous developed algorithm and was found to be consistent at prevailing currency equivalent. The model with entropy scale developed in this study would enable a builder or contactor load iteratively, cost implication of an unseen circumstance even on occasion of deferred cost reimbursement and would help in project cost monitoring. The phenoromone type of cost and entropy generated can be spread iteratively on element's cost so as to forestall overrun and economic variants that can affect project cost negatively.

Key words: Optimization, ant colony, element's, heuristic, entropy, parameter

INTRODUCTION

Importance of shelter in the affairs of mankind cannot be overemphasized; this has made shelter provision an important issue on the agenda of United Nations Organization, through inclusion in the millennium development goal of United Nations Development Programme (UNDP). However, construction industries tend not to be meeting up with the demand of shelter provision world over, resulting from delayed project delivery with few available ones often offered at unaffordable prices, sometimes completed at cost higher than the initially budgeted cost and even abandoned. Moreover, there are factors that often accounts for delayed project delivery among which is inadequate project cost monitoring system. An effective cost monitoring system facilitates the study of minute's details of project cost transactions. However, in the past, regression-based methods have been used and of recent, focus have shifted to using expert systems to facilitate easy monitoring and studying cost movement pattern on a project. Such system includes; fuzzy logic, neural network, ant colony optimization among others. Expert system delivers project cost movement report timely for purpose of project monitoring. Construction industry has been plagued by cost overrun, risk, price fluctuation and the like which often culminates in poor project performance and cost overrun (Amusan *et al*., 2012a, b). However, planners are often faced with the challenge of solving project cost conflict which often arises sometimes while harmonizing project cost with project cost center's entropy. Therefore, a system that could help in cost and entropy trade-off for purpose of obtaining an optimized cost for project cost policy formulation is needed that is a system that would help in studying existing pattern among project cost centers. Cost-entropy trade-off operation follows meta-heuristic optimization thus evolving an expert system that allows heuristic pattern formulation and application to basic pattern study for meaningful deduction like ant colony optimization is needed (Rayes and Kandil, 2005).

Cost-entropy trade-off becomes non deterministic polynomial when formulated mathematically as optimization problems with contingency logics, contingency approach supports multi-parameter application of different solution driven systems in the

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form of non-traditional approximation algorithm like Genetic Algorithm (GA), fuzzy logic, Ant Colony Optimization (ACO) algorithm among others (Lakshiminarayan *et al*., 2010). In recent years evolutionary and meta-heuristic algorithms such as Ant Colony Optimization (ACO) algorithms have been extensively used, considering their attributes such as ease of use, broad applicability and global perspective among others. One of the attributes of ACO is as presented by Dorigo (1992) is described as ability to simulate the ease with which an ant locates a shortest task path to food source, reinforced it to a level it become attractive to other ants even though they are almost blind. However, after >10 years of studies in term of verification of its application effectiveness and theoretical grounds robustness of the ACO in locating and search for an optimum or near optimum solution has been established. This has made ACO a watershed in meta-heuristic applications. To this end, this study has presented the application of ACO as a meta-heuristic technique where the objective was cost-entropy and precedence relationships constraints minimization.

Understanding concept of cost entropy: Entropy could be described as a phenomenon often used to relate the rate of kinetic energy exchange in the matrix of a substance (Amusan *et al*., 2012a, b). It measures the degree of activeness of molecules of a compound. Considering the arrangement of project cost centers on a typical Bill of Quantities (BOQ) of building project, movement of cost disparity in this context typified an entropy movement, therefore, cost entropy could be defined as the measure of restiveness of cost items on the project cost centers of a typical construction project (Amusan *et al*., 2012a). However, probabilistic technique can be used to find the pattern of cost movement through graphs; this pattern is encapsulated in the concept of elemental cost entropy. Elemental cost entropy was described by Christopher (2008) as the study of cost movement pattern among project elements with the aim of identifying cost activeness of the cost centers. Residual cost entropy is described as a measurable concept considering the variable nature which could be evaluated by finding the inverse of probability of cost center being considered (Christopher, 2008; Amusan *et al*., 2012a, b). Moreover, Amusan *et al*. (2012a, b) evaluated cost entropy of selected building project and came up with submissions that entropy could be described as the residual variation margin often obtained through the fluctuating nature of cost centers. Finally, it could be as well measured through determining influence of project cost on the project's final completion cost (Amusan *et al*., 2012a, b).

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 phenoromone 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 phenoromone to make attractive to other ant to follow, they therefore trod the food path based on the amount of phenoromone 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 phenoromone.

However, many researches have been devoted to Ant Colony Optimization (ACO) techniques. ACO is described by Hlaing and Khine (2011) as a method used in allocating non-linear resources and was used to provide solution to travelling salesmans problem, Ying 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 by 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.

Research methods and analytical process: This study used initial and completion cost of (20) reinforced concrete office building projects, initiated and completed within 2008 and 2009, the pre and post economic meltdown period. The bill of quantities of these projects was analyzed based on their elemental dichotomy. 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 by Dorigo (1992), Bell and McMullen (2004), Chaharsooghi and Kermani (2008) in the following order: initialization of solution, heuristic identity formulation, pheromonal updating and renforcement parameters, developing selection probability and defining termination parameters. The development of the algorithm and the analytical process was therefore formatted in the stated order.

MATERIALS AND METHODS

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: $C_e = P^{-1}$ where C_e is cost entropy and P is probability value for the optimized cost option for each project cost centers.

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 phenoromones (Ying and Wang, 2006). The algorithm used in this context is presented in the following order:

1.1 Initialization of cost and entropy function
1.2 Problems graphical representation (Fig. 1)
1.3 Formulating initializing phenoromonal constants
1.4 Repeat for each ant on each cost centers
1.5 Proceed to next node based on transition rule
1.6 Construct a solution
1.7 Reinforce the phenoromone based on updating rule
1.8 Is updating rule fulfilled? Yes? Stop; No? Revert to Step 1.1
1.9 Select the optimized solution

Problem formulation: This study utilized non-linear resource allocation strategy by considering the problem as discrete in nature as advocated by Ying and Wang (2006). 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

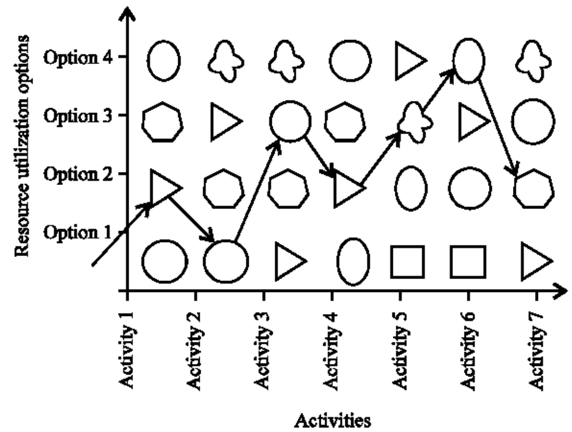

Fig. 1: Ant colony grahical representation of task path (Lakshminarayanan *et al*., 2010)

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:

$$J(x) = \sum_{i=1}^{r} x_k = fi(x_1)$$

Subject to:

$$\sum_{i=1}^{r} x_k = f_i(PC_i) 0 \le a_i \le x_k \le b_i \le Q_i$$

Where:

x_k = An integer and quantity of cost resource allocated to j
f_i = The cost function
Q = Project cost centers
a_i = Regarded as lower boundary of quantity of resource allocated to task i
b_i = The upper bound for quantity of resource allocated to task i

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; phenoromone quantity parameter at the edge ‘i.j,’ αi.j (initial number of cost options) amount of initial quantity of phenoromone (x = 1):

$$\text{Alpha}\,(\alpha) = \frac{\sum_{i=1}^{r} fx_k}{\sum_{i=1}^{r} x_k = f_i(PCo)}$$

PCO is the Project Cost options, when x takes values from 0-1. Rho (P) is the constant that represents vanishing rates of phenoromone, the value can range from 0.49-0.99, the higher the value the stronger the reinforcement of the rail. Also, cost entropy value is denoted by $\eta_{i,j} = 1/d_{i,j}$ where $d_{i,j}$ 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 (β) values represents controlling parameters on selected cost entropy output. The higher the values of α_1 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 by Dorigo (1992) assertion that parameters α and β concentrations determines the pattern of ant's path selection, therefore higher value of the two parameters would make the iterative path selected be more attractive thus influences the concentration of phenoromone. Parameters Alpha (α) and Beta (β) were adjusted till $\beta = 0.01$ while Alpha $\alpha = 1$. ΛT is used to represent concentration of phenoromone deposited during iterations. $\Lambda T = 1/L_{i,j}$ where $L_{i,j}$ equals cost which is taken as function of time.

RESULTS AND DISCUSSION

Results analysis and discussions are presented in this section. Entropy-cost impact matrix scale is summarized in Table 1. Cost entropy impact and values were rated on scale 1-3 with impact value rated on scale 1-3. Low impact carries 1 point, intermediate 2 while very high is rated 3. Cost entropy values were benchmarked in terms of degree of completion in the range 5-100%. Table 2 presents cost-entropy impact matrix dichotomy. Elemental entropy was classified into three dichotomies; High Entropy (HE), Low Entropy (LE) and Intermediate Entropy (IE). Entropy values within range 3, 6 and 9 are regarded as High Entropy (HE) those with entropy values 2, 4 and 6 are regarded as intermediate entropy while low entropy falls within 1 and 3.

Table 3 shows elemental cost entropy threshold. Different elements were considered on Bill of quantity of a residential building project. High entropy is recorded on upper floor elements with index 8.6, roofs (7.0), windows (5.5), doors (5.5), finishing works (15.4), preliminaries (4.9) and VAT (5.2). Low entropy is recorded on the following elements; soil and drainage works, fittings, staircases, frame and walls and substructures, all these have low entropy values that spans 1.1-1.3 while services and contingency have low values of 1.1-1.5. Careful analysis of entropy spread indicates 50% of the cost centers as having low cost entropy value; 28.6% is recorded as being of intermediate status. Appraising the project generally, it can be deduced that there is moderate cost restiveness on the project elements, implications of this is

Table 1: Entropy-cost impact matrix dichotomy

Measurement variable	1	2	3
Cost-entropy impact	Low impact	Intermediate impact	Very high impact
Cost-entropy value	Overall project success <5%	Overall project success <25%	success 25-100% Overall project

Table 2: Cost-entropy influence matrix

	Influence		
Entropy	LE = 1	IE = 2	HE = 3
HE = 3	3	6	9
IE = 2	2	4	6
LE = 1	1	2	3

Table 3: Elemental cost entropy threshold

S/N	Elements	Entropy value	Entropy index
L_1	Substructure	0.015	1.50
L_2	Frame and walls	0.015	1.50
L_3	Staircases	0.015	1.50
L_4	Upper floor	0.086	8.60
L_5	Roofs	0.072	7.20
L_6	Windows	0.055	5.50
L_7	Doors	0.055	5.50
L_8	Finishings works	0.154	15.40
L_9	Fittings	0.018	1.80
L_{10}	Services	0.025	2.50
L_{11}	Soil and drainage	0.011	1.10
L_{12}	Preliminaries	0.049	4.90
L_{13}	Contingency	0.031	3.10
L_{14}	VAT	0.052	5.20

that the project may not likely suffer price fluctuation and can aid builders price monitoring. However, elements with high cost entropy value should be closely monitored, cost elements like upper floor, roofs and finishing works. The high nature of the entropy signifies fluctuations that need to be taken to consideration at bidding stage. The difference can be factored into the initial or bid cost thereby cushion the effect of future price fluctuation on the project.

Table 4 and 5 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 α and β (the initial number of cost options) which are set at 0.01 and 1, respectively ρ (rho) is regarded as phenoromone vanishing constants, $\eta_{i,j} = 1/d_{i,j}$ which represents cost entropy of ant Kth tour. In following shortest route while J(x) which is equivalent to $\sum_{i=1}^{r} x_k = fi(PCi)$ represents quantity of allocated cost to the elements. Entropy is the inverse of the cost centers probability. From Table 4 and 5 highest entropy value occurred on roofs with J(x) value allocation of f152,148 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 phenoromonal trail this indicates that the path of accomplishing this task will be favorable to the imaginary ant 'k' which sought the

Table 4: Ant colony algorithm contingency schedule

Elements	Lower CB	Upper CB	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	90.910
Preliminaries	500,000	550,000	0.045	1.000	0.010	50,000	20.410
Contingency	270,000	280,000	0.031	1.000	0.010	10,000	32.260
VAT	555,929	560,000	0.052	1.000	0.010	4,071	19.230
Sum	217,093,858						

α_1, β_1: controlling parameters $\rho\eta_1$: phenoromone vanishing function; J(x): quantity of allocated cost resource on cost center CB: Cost Boundary

Table 5: 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

tasks in order to complete them. Elements such as substructures, frame and walls, finishing, soil and drainage work has high phenoromone concentration this attracts attention of ants to them thus shortest routes are created to them and are executed quickly, the successful execution of these tasks would guarantee 80% completion of the whole tasks. Those elements with lowest concentration of phenoromone are less attractive, thus could be combined with those of high concentration for total completion of the project tasks.

Table 5 presents validating framework for Ant Colony Optimization algorithm (ACO) developed in the study carried out by Zheng and Ng (2005) MAWA and MOACO were developed with an optimized cost of $173,000 and processing time of 60 sec. Likewise, the MOACO Model developed by Lakshiminarayanan *et al.* (2010) has optimized cost of $165,000. The optimized cost f152,148 was generated in this study through the Cost Entropy Multi-parameters Ant Colony Optimization (CEMACO) algorithm with 53 sec processing time. This is somehow lower than values of previous models.

CONCLUSION

A multi parameter optimization system for cost optimization of reinforced concrete office building cost entropy using ant colony optimization technique has been developed in this study. The model is capable of being deployed in cost-entropy trade-off problem. The study as well developed cost entropy scale for a typical reinforced concrete office building. An optimized cost value generated in this study was compared with cost generated by some selected developed models like that by Lakshiminarayanan *et al.* (2010), Zheng and Ng (2005), it was found to be consistent. The implication of results in this study includes among other things; builders would be at advantage in project cost performance monitoring right from tendering stage and risks on each project element are spread iteratively to avoid sole bearing of risk. The optimized value of f15,418 generated can be spread iteratively on the cost elements with low phenoromone trail as reinforcement. The f152,418 can be allocated as lower boundary and upper boundary cost for each of project cost elements with low phenoromone concentration and entropy. It has been demonstrated that entropy varies inversely with the phenoromone concentration in this study. Elements with low entropy tend to have high concentration of phenoromone and vice versa. Therefore, either of the two parameters could be used in iterative resource allocation to project cost centers. However, further research need to be conducted on factors that influences the phenoromone distribution and entropy disparity on construction projects. The applicability of an ant colony optimization to solving basic cost resource allocation problem on project work has thus been demonstrated in this study.

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