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Time-Cost Trade-Off in Construction Projects using Optimization Approaches

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Abstract—*The important objectives of construction project management particularly time and cost are not independent but internally connected. Considering the trade-off between project duration and total cost is very important; thus improvement method is postulated in project accomplishment. Time–cost improvement is also outlined as a method to develop or speed up the total construction activities by deciding "by how much" in order to define the time-cost optimization, thus to attain the simplest attainable savings in each time and cost. The proposed model adopts fuzzy sets to simulate the degree of uncertainty of the input data. The incorporation of fuzzy sets theory in time cost trade off problem is a smart step to evaluate the decision-making process of human experts in support to the collection of uncertain or incomplete data. Particle swarm optimization along with neural networks has been used as improvement/optimization tools. Totally different risk acceptance level and/or optimism ends up in different programing and scheduling, solution from which the project manager might choose the most well-liked choices.*

1. INTRODUCTION

Due to ever evolving competition among construction corporations, besides owing to the intrinsic challenges related to the development comes, the pre-requisite for a corporation to survive is to perform profound appraisals in preparation of the project schedules. Consequently, uniting the multidisciplinary collaborations and construction firms gets to develop realistic schedules with systematic change techniques. Evidently, any company would fail to meet the anticipated resolutions within the absence of a good schedule.

Almost each construction project involves a completion point in time determined in the contract by the consumer. This date is mostly obtained by network analysis. For such limitations, resource overloads are typically provisioned by recruiting subcontractors or directional various resource supplies. Decision manufacturers speed up the project forcing least further costs by deploying the slack times of the networks on deciding the simplest combination of alternatives for realization of the activities.

This task is completed by providing the simplest balance between the direct and indirect cost of a project, hence the task is exposed to scheduled accelerations.

Siemens (1971) proposed Heuristic Siemens Approximation Methodology (SAM) for time-cost approach that may be a logical systematic approach involving variety of rules for expediting the activities that incur least prices. However it simply considers minimum value slope for crashing activities which may shorten the duration beyond required amount. De et al. (1995) introduced a dynamic programming for time-cost approach which was a centralized approach for deadline problem with no parallel modules and a combination of modular decomposition with incremental reduction approaches for problems with parallel modules. However it was only useful for effective networks with reasonably low values of certain parameters. Feng et al. (1997) introduced Genetic Algorithm (GA) to calculate the fitness values by exploiting minimal distance to convex hull, and by retaining each string for next generation to avoid genetic drift. Neglecting the possible resource constraints is one of the drawbacks as it tackles only finish-to-start relationships. Demeulemeester et al. (1998) proposed branch and bound model for time-cost problem. Horizon-varying approach was embedded into branch and bound method and qualities of lower boundary underestimations were assessed by vertical distance computations. However the effectiveness and efficiency decreases significantly for larger networks with multiple modes. Moussourakis and Haksever (2004) introduced mixed-integer programming model for time-cost approach which requires no network notation system and makes minimal assumptions regarding the type of TCT functions availing subsequent "what if" analysis. It mainly requires substantial computational resources, thus, suits for small to medium networks.

Zheng et al (2005) applied GA that recruits modified adaptive weight approach (MAWA), Pareto ranking, and Niche formation to avoid genetic drift, administer selection pattern, and exert diversifier respectively. Vanhoucke and Debels (2007) proposed meta-heuristic (Exact+Heuristic) for time-cost approach which involves neighborhood search and diversification steps. The second portion of algorithm uses truncated dynamic programming to relax non-critical activities. Elbeltagi et al. (2007) proposed Shuffled Frog Leaping (SFL) and modified SFL algorithms that incorporate a time variant parameter to avoid falling into local optima. Yang (2007) proposed Particle Swarm Optimization (PSO) which is capable of handling any function type which requires manual calculations for subsequent "what if" analysis. However the indirect costs are not provisioned throughout the optimization process. Ng and Zhang (2008) introduced Ant Colony Optimization (ACO) in which Modified adaptive weight approach (MAWA) is integrated into Ant Colony System (ACS).But drawback was probable premature convergence with higher iterations and too sensitive to selection of parameters.

Xiong and Kuang (2008) adopted ACO in which MAWA is embedded into ACS, and selection of the options is made according to membership function, the first selection involving a maximization criterion, and the other incorporating a probability distribution function. Eshtehardian et al. (2008) proposed a method using GA in combination with fuzzy set theory to handle stochastic time-cost trade-off problems (TCTPs). Afshar et al (2009) proposed multi-colony non-dominated archiving ACO (NA-ACO) that assigns separate ant colonies to each objective and evaluates the found solutions respecting the competing objective within the next colony. Anagnostopoulos and Kotsikas (2010) proposed a method based on Simulated Annealing (SA), in which the performance was mainly based on the five variants of SA algorithm in the set of activities in a network and the results were analyzed and compared to each other. Zhang and Xing (2010) applied PSO for time-cost and quality approach involving a fuzzy-based PSO with quality considerations that employ fuzzy attribute utility to generate composite values. But it generates only a single optimal solution rather than the Pareto front. Sonmez and Bettemir (2012) proposed a hybrid GA by combining potencies of SA along with quantum simulated annealing (QSA). Ashuri and Tavakolan (2012) introduced hybrid GA-PSO for time-cost and resource (TCRO). It is a fuzzy-based hybrid GA-PSO with resource considerations that treat lower and upper halves of population using GA and PSO, respectively. It mainly handles only TCRO problems with continuous functions.

2. PROBLEM STATEMENT

The main objective of this study is to present a progressive model with improved accuracy, that is capable of exerting the time-cost curve drawback, i.e., distinctive variation for larger discrete Time-cost Trade-off (TCT) networks.

3. MODEL FORMULATION

The proposed model is formulated as follows.

i. Construction of the project network.
ii. Identification of the paths in the network passing through the initial and final activities.
iii. Evaluation of the cost slopes (cost per unit of time saved) for the activities in the network.
iv. Measurement of the completion time for the identified paths.
v. Determination of the longest path i.e. the critical path. If more than one choice exists, discrimination is made in favor of the path having smaller least cost slope.
vi. Detection of the activity with least cost slope within the selected critical path. If cost slope is common to more than one activity, discrimination is made in favor of the activity which is common to greater number of paths. If more than one choice still exists, discrimination is made in favor of activity that permits greater amount of expedition.
vii. Expedition of the detected activity by the available amount of duration.
viii. Re-iterations of steps (iii) through (vii) until all the activities of the selected critical path are crashed.

4. PROBLEM DEFINITION

The objective of a time cost optimization problem is to minimize the total cost obtained by set of activities to shorten the total duration in order to obtain the targeted results. This can be done using Particle Swarm Optimization (PSO). The objective function defined is

$$Minimize \sum_{\forall i} C_i \tag{1}$$

And the total evaluation is based on fitness functions subjected to the constraints

$$D_i = \max\left[\sum_{j=1}^{s}\sum_{k=1}^{m} d_{jk}^{(t)} x_{jk}^{(t)}\right] \tag{2}$$

$$C_i = \sum_{j=1}^{s}\sum_{k=1}^{m} dc_{jk}^{(t)} x_{jk}^{(t)} + D_i \times ic \tag{3}$$

$\forall j = \{1,...,s\}$, $\forall k = \{1,...,m\}$, and D_i and C_i represent the total duration and the total cost of the i^{th} particle, d_{jk} represents the duration of the k^{th} options for the j^{th} activity; x_{jk} represents position of the particle for the k^{th} option for j^{h} activity, dc_{jk} denotes direct cost k^{th} alternative of the j^{th} activity and ic denotes the daily indirect cost.

The fitness evaluation of the particles, the optimality of the solutions are compared with each other regarding condition

$$u > v \text{ If } C_u \le C_v \tag{4}$$

This determines discrimination which is made in favor of decision vectors, in case the total project cost of that particle is less than or equal to decision vector v; i.e., $C_u = C_v$ discrimination is generally considered in favor of the particle having lesser duration.

$$u > v \ \text{ if } \begin{Bmatrix} C_u = C_v \\ D_u < D_v \end{Bmatrix} \tag{5}$$

Later, in considering the inertia weight, the velocity of the particle is calculated to determine time variant reduction as a parameter to enhance better balance between the local and global searches (Kennedy and Eberhart 1997).

$$v_{ijk}^{(t+1)} = w^{(t)} v_{ijk}^{(t)} + c_1 r_1 \left(p_{ijk}^{(t)} - x_{ijk}^{(t)} \right) + c_2 r_2 \left(p_{gjk}^{(t)} - x_{ijk}^{(t)} \right) \tag{6}$$

The measured velocities are transformed to probabilities and are margined from the range of 0 to 1 using logistics transformation.

$$sig\left(v_{ijk}^{(t)}\right) = \frac{1}{1 + \exp\left(-v_{ijk}^{(t)}\right)} \tag{7}$$

Each particle is then shifted to new position based on the probabilistic condition (Izakian et al. 2009, 2010).

$$x_{ijk}^{(t+1)} = \begin{Bmatrix} 1 \\ 0 \end{Bmatrix} \ if \ \begin{matrix} sig\left(v_{ijk}^{(t+1)}\right) = \max\left\{ sig\left(v_{ijk}^{(t+1)}\right)\right\} \\ otherwise \end{matrix} \tag{8}$$

5. APPLICATION AND ANALYSIS

Illustration and analysis are done for the proposed model on the set of data consisting of eighteen activities. Each set has three to five options (Considered from Eshtehardian et al. 2009). The obtained data has three sets of time and cost for each activity, in which first and third value in the data is small and large respectively. The middle value considered is more probable/feasible for time and cost. The indirect cost is considered as 1500$/day. Analysis is carried out by considering PSO assuming indirect costs of 0, 200$/day and 1500$/day.

The system initializes with a population of random potential solutions. The population is hailed as "swarm", while, the potential solutions are termed as "particles". The particles are flown through a multidimensional search space. Particles iteratively fly over the search space in explicit directions, and are attracted to self-attained historical best position (personal best; pbest) and to the best position among the entire swarm (global best; gbest). Each particle memorizes the coordinates associated with the best location it has visited so far. At each time step, particles evaluate their own positions with respect to definite fitness criteria, then, comparing the fitness values, they communicate to identify the particle located in the best position. Henceforth, aiming to imitate the best bird, each bird speeds towards the best position using a velocity that incorporates coordination of the personal best location. Accordingly, at any iteration, velocity of each particle is adjusted depending on random terms, with independent random numbers being generated for acceleration toward personal and global bests. Each particle, then, evaluates the domain from its new location, and the process reiterates until either the swarm reaches to a predefined target, or a computational limit. Considering the numbers of variables, PSO randomly positions particles in a non-dimensional solution space (Kennedy and Eberhart 1997) as shown in Fig. 1.

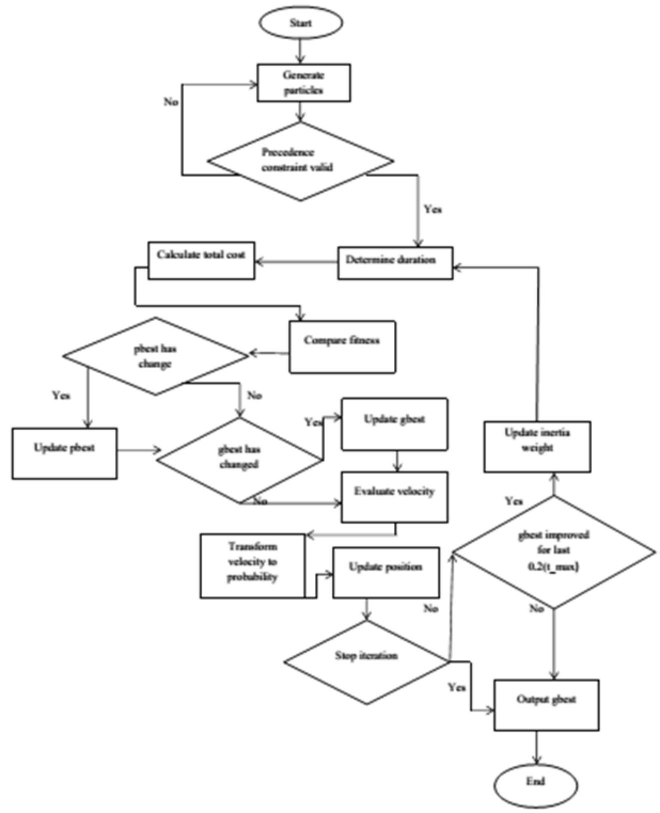

Fig. 1: Flow chart showing the procedure for PSO analysis

6. RESULTS AND DISCUSSION

The main purpose of these tests is to find the effect of selected parameters to analyze overall performance of the considered data. As a final result, the selected parameters have been fine-tuned through a sequence of trial and error assessments, with respect to the convergence speed and the total quality of the solution. The last operators set for every approach, iterations (t), particles(i), c_1 and c_2 inertial weight (w), and $v_{\max}$ are given in the sequence . The practiced instances are some of the best known time-cost trade-off (TCT) issues analyzed in the development of construction management. The three extensions of discrete TCT data are fed into PSO optimizers, and experiments are directed to validate their competencies in order to update the satisfied results.

The test problem involves the 18-activities derived from Feng et al. (1997), Eshtehardian et al. (2009), incorporating the time-cost alternatives defined in Hegazy (1999). This instance is widely followed by numerous researchers (Elbeltagi et al. 2005, Zheng et al. 2005, Elbeltagi et al. 2007, Ng and Zhang

2008, Xiong and Kuang 2008, Afshar et al. 2009, Sonmez and Bettemir 2012) to compare the performance of their experiments. Three sample checks has been carried out to be adopted in discrete PSO model. Obtained results ensure the robustness of the proposed model compared to that of other advanced models, in addition to the exact process. For the time-constraint TCT evaluation, a 3rd test result based on the performance of 18-activity is used. This instance incorporates liquidated damages and incentive payments with reference to a predetermined value of entirely cut-off data. This instance has been carried out to achieve results and to affirm the efficiency of the proposed version, providing sound answers within a small processing time as presented in Table 1.

Figures 2–4 show the results, interpreted by plotting the graph for 3 different indirect cost values. Which in turn shows the variation of duration and cost with respect to indirect cost. First test is carried out considering indirect cost as 0, there was minimum cost for the maximum duration. Second test was for the indirect cost of 200$ in which the result was quite acceptable. For the third test with indirect cost of 1500$ the obtained results are optimal as the cost and duration both were in feasible range. Hence the third result was tabulated and compared with the results of previous adopted models.

Table 1: Analyzed data of different indirect costs

No. of analysis	Indirect Cost ($)	Duration (days)	Cost ($)	APD (%)	Average CPU time (s)
10	0	169	99450	0.00	0.08
10	200	126	128150	0.00	0.08
10	1500	110	271150	0.00	0.08

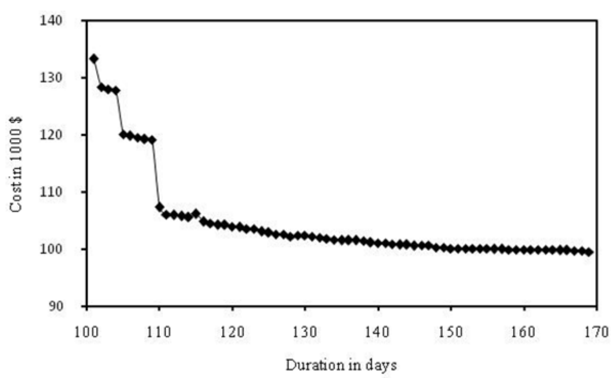

Fig. 2. Solution for indirect cost of zero dollar

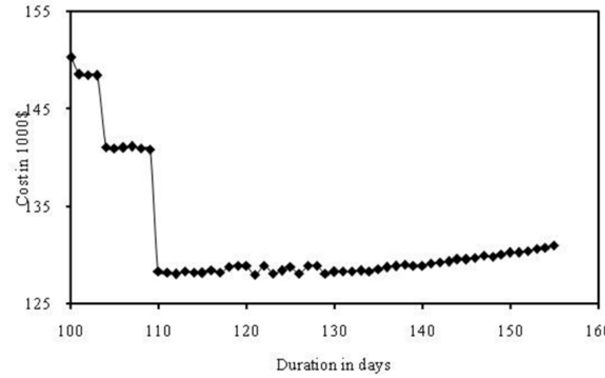

Fig. 3. Solution for indirect cost of $200

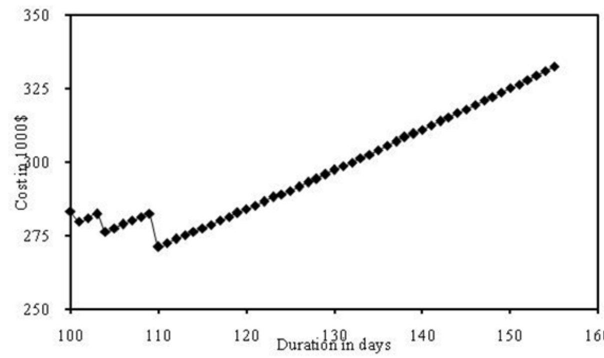

Fig. 4: Solution for indirect cost of $1500

7. CONCLUSION

Compared to the solutions of other developed model along with the most effective answer obtained from the actual approach, it's evident that the proposed discrete PSO model is effective in finding the best or near-optimum solutions for the medium-sized available data with insignificant deviations from the nearest solutions. It's been observed that the quality results for increase in duration slightly deteriorate as indirect cost is increased. Also this model operates within acceptable processing time by looking merely small fractions of the quest space. As a result, the proposed model has been found to outperform all the earlier optimizers with reference to both the convergence speed and the feasible solutions. However it is difficult for meta-heuristic model, to obtain the satisfactory results with the same procedure.

The other paradigm of the discrete PSO, set of rules has been brought within the context of this work to obtain the answer for the time-constraint TCT issues. Minor adjustments specifically done to the fitness capabilities were implemented to the previously targeted particle swarm optimizer. Executed revisions are made enhancing assessment of problem with provisions for incentives and liquidated damages. The performance of this model has been confirmed in presenting sound solutions throughout the analysis. The optimality of the solutions obtained after experiments has been demonstrated and compared with the outcomes of the exact process. Hence the proposed model has been validated concerning the previous optimizers for its convergence competencies.

Despite shortcomings of the project model, requirement stays with ways to incorporate resource availability throughout analysis.

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