APPLYING THE SHUFFLED FROG-LEAPING ALGORITHM TO IMPROVE SCHEDULING OF CONSTRUCTION PROJECTS WITH ACTIVITY SPLITTING ALLOWED

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Abstract

In situation of contractors competing to finish a given project with the least duration and cost, acquiring the ability to improve the project quality properties seems essential for project managers. Evolutionary Algorithm (EAs) have been applied as suitable algorithms to develop the multi-objective Time-Cost trade-off Optimization (TCO) and Time-Cost-Resource Optimization (TCRO) in the past few decades ; however, by improving EAs, the Shuffled Frog Leaping Algorithm (SFLA) has been introduced as an algorithm capable of achieving a better solution with faster convergence. Furthermore, considering splitting in execution of activities can make models closer to approximating real projects. One example has been used to demonstrate the impact of SFLA and splitting on the results of the model and to compare with previous algorithms. Current research has elucidated that SFLA improves final results and splitting allows the model find suitable solutions.

Keywords: Optimization, Multi-objective SFLA, Splitting, Leveling, Construction Management

INTRODUCTION

Project control plays an important role for contractors for scheduling, cost analysis and resource evaluation. The time and cost of projects are related to each other and considered in Time-Cost trade-off problems. From the researchers' point of view, developing highly efficient and robust algorithms to solve highly complex Time-Cost trade-off problems is still a challenging subject (Afshar et al. 2009). On the other hand, the challenge in resource leveling problems is to make the resource requirements as uniform as possible and to force resource utilization to conform to a desired, predetermined resource distribution in order to meet the project milestones (Senouci and Eldin 2004). In addition, resource availability constraints may postpone activity start time, extend activity duration, and hence prolong the total project duration (LU and Lam 2008).

One of the factors that has significant impact on completed time and cost of project is delay. Delays are acts or events that extend the time necessary to finish activities under a contract (Stumpf 2000). If a project is delayed beyond its due date, a financial penalty is incurred by the contractor (Vaziri et al 2007). Delays during execution of projects can happen at the start of each activity or during activities. Delays at the start of activity change the initiation from early start to late start. If an activity is placed on Critical Path Method (CPM) or delay duration is longer than total float, then delay postpones project duration. We call it "splitting allowed" if delay happens during activity execution. It effects on total duration of activity, however, the active duration of activity will not be varied.

Accordingly, the key question is how to allocate resources to activities while taking into account splitting, in order to finish the project within budget and on time from the standpoints of contractors, sponsors, and the project client.

RESEARCH BACKGROUND

In an attempt to reduce processing time and improve the quality of solutions, particularly to avoid being trapped in local optima, Evolutionary Algorithms (EAs) have been introduced during last decade (Elbeltagi et al. 2005). EAs are stochastic search methods that mimic natural biological evolution and social behavior of species. One of the most important criteria of EAs is their capability of speed convergence to obtain a global optimized solution. Based on Elbetlagi's work (2005), the best solutions of TCO problems have been received by the Shuffled Frog Leaping Algorithm (SFLA). SFLA presented by Eusuff and Lansey (2003) is a meta-heuristic iterative method inspired from the memetic evolution of a group of frogs when seeking for food (Huynh 2009). In the SFLA, the virtual frogs are periodically shuffled and reorganized into new memplexes in a technique similar to that used in the Shuffled Complex Evolution algorithm (SCE) in order to ensure global exploration. The results demonstrated that SFLA produced better results than the Genetic Algorithm (GA) in terms of effectiveness and efficiency for all problems.

SHUFFLED FROG LEAPING ALGORITHM

Instead of using genes in GA, SFLA uses memes to improve spreading and convergence ratio. Meme (pronounced 'meem') is a contagious information pattern that alters human/animal behavior. The actual contents of a meme, called memotype, are analogous to the genes of a chromosome (Eusuff 2004). The main difference between a gene and a meme is related to its transmission ability. Genes can only be transmitted from parents or a parent in the case of asexual reproduction to offspring. Memes can be transmitted between any two individuals (Eusuff 2006). SFLA, in essence, combines the benefit of the local search tool of Particle Swarm Optimization (PSO) and the idea of mixing information from parallel local searches, to move toward a global solution which is called a Shuffled Complex Solution (SCE). The philosophy behind SCE is to treat the global search as a process of natural evolution (Duan et al 1992). On the other hand, PSO simulates a social behavior, such as bird flocking, to a promising position for certain objectives in a multidimensional space (Kennedy and Eberehart 1995). A population of particles is randomly initialized with position and velocities. The particles are improved according to the following equations:

$$\nu_i(t+1) = w*\nu_i(t) + c_1*r_1*(P_i(t)-X_i(t)) + c_2*r_2*(P_g(t)-X_i(t)) \quad (1)$$

$$X_i(t+1) = X_i(t) + \nu_i(t+1) \quad (2)$$

where w=inertia coefficient, which has an important role in balancing a global (a large value of w) and local search (a small value of w); c_1 and c_2=constants ; r_1 and r_2 =uniform random numbers in [0,1]; P_i=best position vector of particle *i* so far ("personal" best); P_g=best position vector of all particles so far (global best); $X_i(t)$ =current position vector of particle *i*; and $\nu_i(t)$=current velocity of particle *i*.

The whole population of frogs is distributed within a different subset called a memeplex. Each memeplex is considered a different culture of frogs, performing an independent local search. After a defined number of memetic evolutionary steps, frogs are shuffled among memeplexes, enabling frogs to interchange messages among different memplexes and ensuring that they move to an optimal position, similar to particles in PSO. The local search and the shuffling processes continue until defined convergence criteria are satisfied (Eusuff 2006). Figure 1 demonstrates the flowcharts of the SFLA. (See Eusuff-2004-for a comprehensive review of SFLA algorithm)

TIME-COST-RESOURCE OPTIMIZATION MODEL WITH ACTIVITY SPLITTING ALLOWED

Each frog in the TCRO model consists of *p*4* memes, in which *p* is the number of activities. Selected option and early start date can be placed as values of two first memes for each activity. After fixing CPM for each frog, Total Float (TF) and Free Float (FF) are calculated for each meme and are placed as values of the next two memes for each activity. In cases of splitting

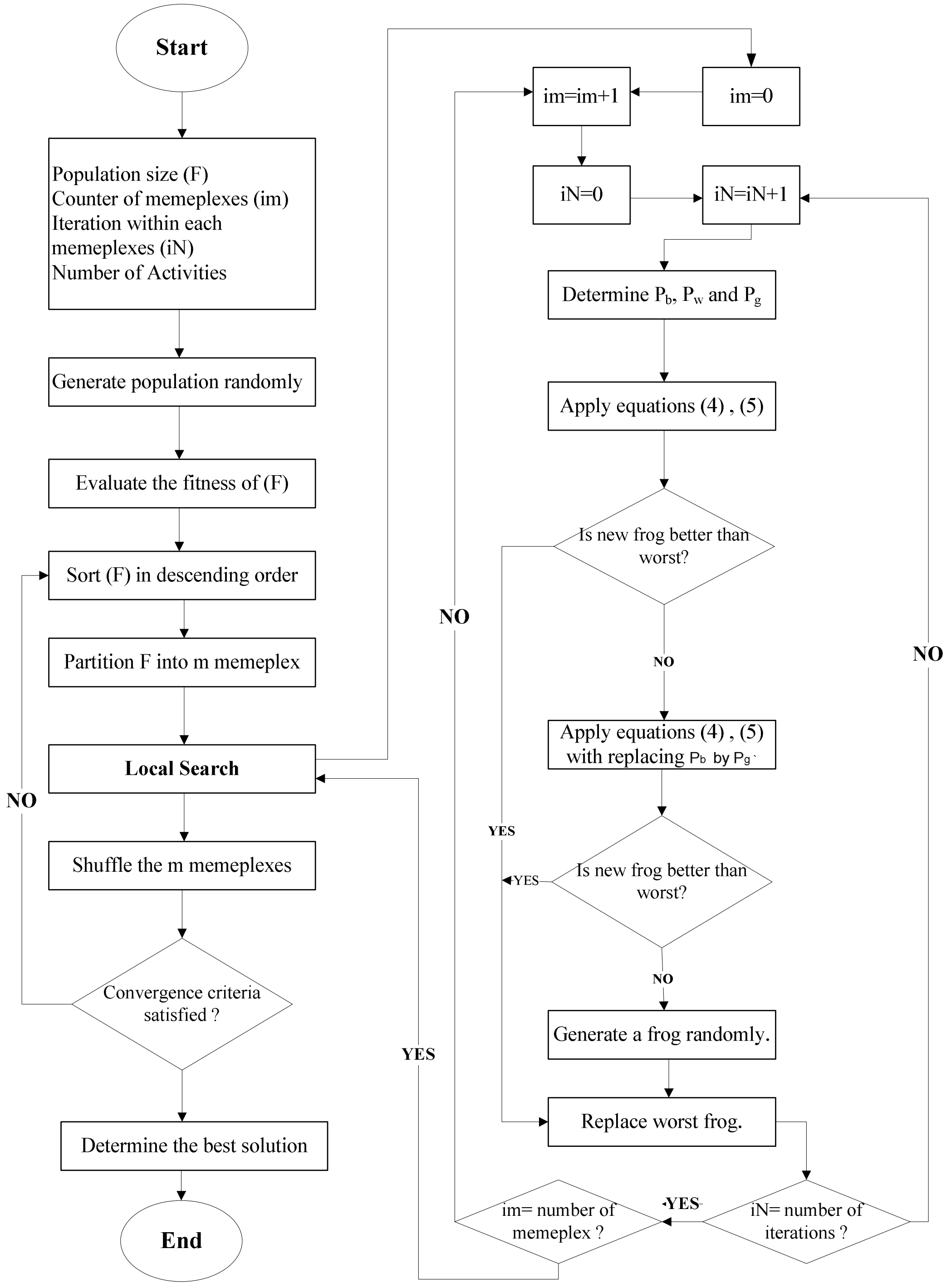

Figure 1. *The flowcharts of the SFLA*

allowed, these values will be used to optimize objective functions. The sequence of memes should be consistent with the order of activities in priority relations between activities. Each frog contains the information of one project based on the different chosen option of activities. Six main parameters are estimated for each frog.

- Critical path for estimating total duration of project execution;
- Total time of project;
- Total cost of project;
- Moment of resources;
- Logical parameter which shows validity of Daily Resource Limit (DRL) condition;
- Activities of project in which splitting has been applied to optimize objective functions;
- The binary parameters should display the active duration of each activity based on the selected option.

OBJECTIVE FUNCTIONS

The objective functions of the TCRO model are formulated to simultaneously minimize total project time and cost along with leveling and allocating of resources to different activities. (Zharaie and Tavakolan 2009). Based on Hegazy (1999), three resource moments have been applied based on the goal of the project manager in utilizing resources.

1. In order to reduce of fluctuations in utilizing resources (M_1):

$$M_1 = Min\left(\sum_{j=1}^{m}\sum_{i=1}^{n} r_{ij}^2\right) \quad (3)$$

Where *r* is the resource utilized in day *i*; and *m* and *n* are total number of resources and days required for project execution, respectively.

2. In order to release the resources in the least possible time (M_2):

$$M_2 = Min\left(\sum_{j=1}^{m}\sum_{i=k}^{n} (r_{ij} \times (i - k_j))\right) \quad (4)$$

Where k_j is the start time of using each resource.

3. In order to reduce fluctuations of resources utilization and release of resources in the least possible time (M_3):

$$M_3 = Min\left(\left(\sum_{j=1}^{m}\sum_{i=1}^{n} r_{ij}^2\right) + \left(\sum_{j=1}^{m}\sum_{i=k}^{n} (r_{ij} \times (i - k_j))\right)\right) \quad (5)$$

One of the above mentioned resource allocation objectives and the two following objectives of minimizing total time and total cost of project are the three objective functions of the optimization model:

$$M_4 = Min\ Z_c \quad (6)$$

$$M_5 = Min\ Z_t \quad (7)$$

CONSTRAINTS OF THE MODEL

The main constraint of the model considered is the fact that the structure of the model is related to the dependencies between activities. In other words, the relationships of the activities cannot be changed in a network of activities. Since we have only “Finish to Start” relationships between activities, the following constraint precludes the situation that the successor has started before the predecessor is finished by considering TF and FF of all activities in one frog.

$$(TF_p - FF_p - m + 1) * \lambda_{km} + \lambda_{p(Dp+FFp+m)} + \lambda_{p(Dp+FFp+m+1)} + \ldots + \lambda_{p(Dp+TFp)} \leq (TF_p - FF_p - m + 1) \quad (8)$$

where m=1,2, . . . ,$TF_p - FF_p$.

Another important constraint that should be considered in the model is the Daily Resource Limit (DRL) condition. Where resources are allocated, the logical parameter should be considered in order to level resources. Considering splitting for noncritical activities gives the model more flexibility to optimize Pareto front solutions. Based on Son and Mattila’s research (2004), the binary optimization model must reflect the duration constraint for each activity.

EXAMPLE

In order to demonstrate the effectiveness of SFLA on the TCO and TCRO models with splitting allowed, one example is adapted from Zheng and Ng (2005). It contains seven activities. The daily indirect cost of this project is considered to be $1500, the same as prior research on this example. In total, 80 options have been considered for seven activities of the project. As Tables 1 and 2 show, 7 required resources with fixing unit costs (ranges from $50 to $4000) and defined number of options during construction have been considered for different activities of project.

RESULTS OF EXAMPLE

SFLA applied on this example demonstrates improvement of results of the TCO and TCRO model. For local exploration, the parameters of c_1 and c_2 in the equation (1) are set to 2. The value of inertia weight w is stipulated at 0.5. Results are evaluated in both splitting allowed and not allowed. Before applying splitting, results of TCO and TCRO are compared with the previous works in terms of non-dominated solutions and processing time of convergence. The

Table 1: *Details of Example*

Activity Description	Activity Number	Precedent Activities	No. of Options	Types of Required Resources
Site preparation	1	-	11	7
Forms and rebar	2	1	11	4
Excavation	3	1	19	4
Precast concrete girder	4	1	9	7
Pour foundation and piers	5	2,3	9	7
Deliver PC girders	6	4	11	7
Erect girders	7	5,6	10	7

Table 2. *Different options for the first activity in Example*

Option No.	Duration	Number of Required Resources							Total Cost($)
		R1	R2	R3	R4	R5	R6	R7	
1	14	3	2	1	1	1	0	0	23000
2	15	3	2	1	0	1	2	0	21900
3	16	3	2	0	1	0	1	2	20800
4	17	3	2	0	0	1	1	0	19700
5	18	3	1	1	0	1	2	4	18600
6	19	3	1	1	0	0	0	0	17500
7	20	3	1	0	0	1	2	0	16400
8	21	2	2	0	0	0	1	2	15300
9	22	2	1	1	0	1	1	0	14200
10	23	2	1	0	1	0	0	2	13100
11	24	2	0	0	2	2	0	0	12000

results demonstrate that the least cost and fewest resource moments are decreased by SFLA. In addition, the processing time to obtain a final solution is improved by 25%, however, only least time and cost solutions are decrease in the TCRO model and resource moments solutions have not been changed by SFLA. The processing time is improved by 22% in TCRO model.

The other objective of selecting this example is comparing results when splitting is applied in the model. In order to apply splitting in activities, the values of TF and FF of each meme can be used. The results demonstrate that the time and cost are decreased by 6% and 0.4% respectively in TCO model and 6% and 0.3% in TCRO. The same procedure can be seen in resource moments solutions. They are improved by 0.07% to 1.8% by applying splitting in SFLA in both TCO and TCRO models. Compared to cases without splitting, the processing time increases in both models. It should be noted that every results in this example is considered with an unlimited resource condition. Table 3 shows the complete results of this example.

Table 3. *The results of Example*

Model		Algorithm	Splitting	Pop. Size	Min Time	Min Cost	Minimum Resource Moment among the pareto solution			Average of Processing time (min)
							M_1	M_2	M_3	
Zheng et al. 2004		GA	Not Allowed	5	66	236,500	-	-	-	-
Zahraie & Tavakolan (2009)	TCO model	NSGA-II	Not Allowed	250	65	226,350	8,539	98,120	41,057	12
TCO model		SFLA	Not Allowed	250	64	226,300	8,535	98,050	40,522	9
TCO model		SFLA	Allowed	250	61	225,450	8,405	96,201	39,982	13
Zahraie & Tavakolan (2009)	TCRO model	NSGA-II	Not Allowed	500	69	228,750	4,769	54,585	13,059	18
TCRO model		SFLA	Not Allowed	500	65	227,250	4,637	53,843	12,863	12
TCRO model		SFLA	Allowed	500	64	226,850	4,601	53,361	12,068	18

CONCLUSION

SFLA has been used as appropriate tools to obtain the best solutions with the least total time and cost by evaluating unlimited possible options. One of the problems of previous research is that assumptions make them unrealistic in comparison with actual construction projects. On the other hand, delay events during execution of activities have an important impact on total time and cost of projects. Therefore, the authors attempt to make the model better approximate real projects by considering splitting during execution of activities.

The example is adapted from Zheng and Ng (2005) to compare non-dominated solutions of SFLA by applying splitting to previous works in GA and NSGA-II. Results in both TCO and

TCRO models demonstrate improvement of solutions, convergence ratio, and the processing time to reach the optimum solution. It confirms that SFLA improves results, by comparing results before applying splitting. Moreover, splitting permits the model to become more flexible in finding the least time and cost and the fewest resource moments. Since in this case, we do not have any limit for resources, the impact of splitting on concepts of time-cost trade off and resource allocation has been investigated. The values of improvement demonstrate that splitting has significant impact on final results.

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