PROJECT PLANNING WITH CONSTRAINT RESOURCES USING ACCELERATED PARTICLE SWARM OPTIMIZATION

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Abstract- In this research, our goal is to propose an approach for optimized resource scheduling considering multiple criteria. In the proposed approach tree objective functions including makespan, execution cost and resource deviation are used. To solve the problem, Accelerated Particle Swarm Optimization (APSO) with chaotic local search is proposed. The proposed approach is evaluated for scheduling two different scale problems. The experiments show that the proposed approach results in more non-dominated solutions compared to another multi-objective approach namely NSGA II.

IndexTerms- Constraint Resource Scheduling, Accelerated Particle Swarm Optimization, Chaos Theory.

I. INTRODUCTION

Construction projects consist of complex activity network with precedence relationship among the activities, in which each activity can be performed in one of several execution modes. Each mode represents an alternative combination of resource requirements of the activity with related duration for accomplishment. In other words, project scheduling mechanism is an actual execution of the plan and tries to deliver its optimal performance into sequence of activities to be executed. In today's competitive business environment, companies cannot survive without efficiently planning and scheduling. Critical path method (CPM) is widely used for project planning and scheduling in construction projects. It takes into account the time and determines critical activities to minimize project makes pan, but the resource availability is not considered. This is however impractical, because in a real project resource availability and allocation will affect the entire project scheduling. To overcome CPM major limitations, several techniques and optimizations have been proposed in project management and scheduling literature and usually can be classified in four categories: resource constraint scheduling, time cost trade-off, resource leveling and resource allocation. It is a strongly NP-hard problem and for complex networks only efficient heuristics and meta-heuristics can obtain optimal/near optimal solutions.

In this paper, the idea is to develop a multi-mode resource constrained discrete time-cost-resource optimization model that considers all the mentioned criteria simultaneously. Therefore the proposed model constitutes three objectives including minimum duration, minimum cost and minimum resources moment deviation on the project makespan. To solve this problem Accelerated Particle Swarm Optimization (APSO) is proposed which is enhanced using chaotic theory.

Recently, meta-heuristic approaches have gained popularity for optimization problem solving. These approaches apply random initialization and evolution of solution population for this purpose. These approaches have also been used in scheduling problem already. Some of these approaches used in this context are Simulated Annealing, Genetic Algorithm, Tabu search, Ant Colony Optimization, Particle Swarm Optimization and so on. In [1] an approach based on Fuzzy logic and Genetic algorithm is used for job shop scheduling problem. Reference [2] used a modified multi-objective GA for scheduling problem. In [3] a modification on mutation and crossover on GA algorithm is applied for better convergence.

The rest of this paper is organized as follows. Section 2 introduces the proposed approaches. Section 3 discusses the experimental results and evaluations. Finally, Section 4 concludes the achievements and proposes future works.

II. PROPOSED MODEL

In our problem each activity j can be executed in one of M_j modes and if activity j is executed in mode m, r_{jm} resources are required and the direct cost of executing the activity is c_{jm}. Also the duration of executing j in mode m is denoted by d_{jm}. When activity j begins, any interrupt is disabled. Also the resources are limited and in any time we have R_k resource of type k. To determine the cost of a possible solution three different functions including the total completion time, total cost and resource deviation is proposed in this paper.

The first function used in this model in the total completion time which is set equal to the makespan and is denoted by F_t:

$$F_t = f_j \quad (1)$$

The second function is the total project cost which is defined as follows [5]:

$$F_c = \sum_j \sum_{m \in M_j} (x_{jm} \times c_{jm}) + y_j \times c_p \times (f_j - T_{contract}) \quad (2)$$

In which x_{jm} means that activity j is executed in mode m. In the above equation, the second term denotes the cost of lengthening the project more than the specified

contract time, in which $T_{contract}$ is the contract time. Also y_J suggest if the makespan is more than $T_{contract}$. Also, to measure the fluctuations in resource utilization, another objective function is defined as the standard deviation of resources in which $r_k(t)$ denotes the utilization of resource k in time t and K and T are the total resources of the project and the total project time, respectively.

$$M_x^{devdox} = \sum_{k=1}^{K} \sum_{t=1}^{T} (r_k(t) - \bar{r}_k)^2 \quad (3)$$

In which $\bar{r}_k$ is the mean resource utilization. Ultimately the combinational objective function of the proposed model is computed as follows:

$$Cost = F_t + F_c + M_x^{dev} \quad (4)$$

A. Problem Encoding

The goal of the proposed approach is to find a proper sequencing and execution mode of jobs so that some objectives as fulfilled. Therefore the variables of a solution are divided to two parts. The first part shows the sequence of jobs identifiers and the second part denoted the execution mode of the jobs. In the proposed encoding each solution is demonstrated by a vector of length 2*N where N is the total number of activities.

B. Accelerated particle swarm optimization for scheduling

A novel and modified PSO by the name of Accelerated Particle Swarm Optimization (APSO) is utilized in this study, which benefits from high rate of convergence to the global optimum. In APSO model the velocity vector is updated by equation (5).

$$v_i^{t+1} = v_i^t + \alpha r(t) + \beta(g^* - x_i^t) \quad (5)$$

In which r(t) is the standard Gaussian distribution N(0.1), v_i^t is velocity of i^{th} particle in t^{th} iteration, g^* is the best position within the swarm and x_i^t is the position of the i^{th} particle in t^{th} iteration. To increase the convergence rate of PSO and enhance it, the velocity parameter is removed and the equation to update the position of each particle in APSO is defined as Eq. (6).

$$x_i^{t+1} = (1 - \beta)x_i^t + \beta g^* + \alpha r \quad (6)$$

In Eq. (6), αr is the parameter to escape from local optimum. r and α values are determined based on standard Gaussian distribution.

C. Chaotic Accelerated particle swarm optimization

The only variable parameter in APSO is β. β significantly affects the convergence rate and also APSO algorithm's behavior. If β is equal to 1 the algorithm rapidly converges as it finds a local minimum. Utilization of chaotic maps leads to an increase in convergence rate of APSO to reach the overall optimum. Determination of β value using chaotic maps also increases the rate of convergence to the overall minimum (i.e. with relatively less iterations). In this study logistic chaotic maps is used for chaotic number generation.

III. EXPERIMENTS

This section concerns the evaluation of the proposed approach. The simulations are performed in MATLAB environment. For evaluations and comparisons the benchmark problems is in [4, 5] is used in the section.

The first problem which is illustrated in Figure 1 and Table 1 is a problem with 6 tasks. Figure 1 shows the precedence graph of these tasks and Table 1 shows the specifications of the tasks including execution modes, execution time, required resources and direct execution cost. In the first problem the available resource is 4, the indirect cost for each day is 500, the maximum execution time is 18 days while the cost per extra day is 1000.

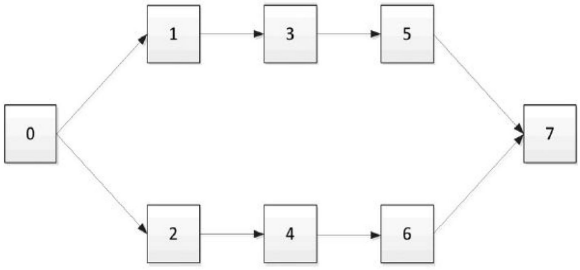


Figure 1.Precedence graph of the first problem [4, 5]

Table 1. The specifications of the first problem [4, 5]

ID	mode	Duration	Resource requirements	Direct cost
1	1	3	2	5
	2	4	1	1
2	1	2	3	6
	2	4	3	2
3	1	2	4	2
	2	3	2	2
4	1	2	3	6
	2	2	4	4
5	1	3	3	1
	2	3	1	7
6	1	4	2	1
	2	6	1	1

The second problem which is illustrated in Figure 2 is a much larger problem with 37 tasks. Figure 2 shows the precedence graph of these tasks. In this problem the available resource is 12 and the indirect cost for each day is 100, while there is no constraint on the finishing time.

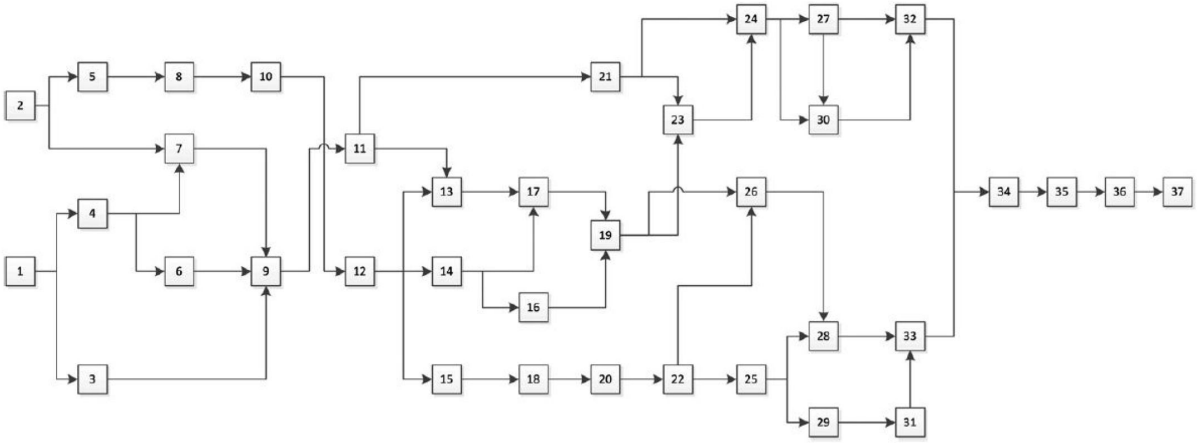


Figure 2. Precedence graph of the second problem [4, 5]

A. Experimental Results

The evaluation criteria are the same as stated in Section 2. For the proposed approach the parameters are set as stated in Table 2.

Table 2. Parameters of the proposed APSO algorithm

parameter	Value
population size	50
No. of iteration	100

Table 3 shows the results of the proposed approach in comparison with the NSGA II method in [5] on the first problem. In this table the result of NSGA II approach shows the non dominated solutions while the results of the proposed approach show the best solution. These experiments show that proposed approach end in a similar solution in a simple and small problem which is equal to the best solution of NSGA II in [5].

Table 3. The results of the proposed approach compared to NSGA II proposed in [5] on the first problem

Search Strategy	Solution No.	makespan	Execution time	resource deviation
NSGA II	1	12	17000	2.25
	2	10	22000	2.1
	3	13	22500	1.68
proposed CAPSO	1	12	17000	2.25
	2	12	17000	2.25
	3	12	17000	2.25

Table 4 shows the results of the proposed approach in comparison with the NSGA II methods in [5] on the second problem. In this table the result of NSGA approach shows the non dominated solutions while the results of the proposed approach show the best solution. This experiment shows that in a large problem spaces each approach lead to different solutions. However, again the proposed approach dominates the NSGA II algorithm from both execution time and resource deviation point of view.

Table 4. The results of the proposed approach compared to NSGA II proposed in [5] on the second problem

Search Strategy	Solution No.	makespan	Execution time	resource deviation
NSGA II	1	190	147700	2719.27
	2	191	147200	2721.58
	3	192	146400	2587
proposed CAPSO	1	168	148800	995.94
	2	158	148400	784.33
	3	156	147600	852.83

CONCLUSIONS

In this paper a chaotic ICA approach for effective restricted resource project scheduling is proposed. In this paper a new encoding for the problem is proposed and the objective function is defined as the combination of three functions namely project make span, project cost and resource deviation. Also the approach is evaluated on two different scale problems as suggested in [4, 5]. The experiments show better performance of the proposed approach compared to the multi-objective NSGA II. As the future works we propose the use of other pareto-based optimization problems and a modification on the initialization to have less duplicate and incorrect initial population.

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