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Discrete particle swarm optimization method for the large-scale discrete time–cost trade-off problem

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ABSTRACT

Despite many research studies have concentrated on designing heuristic and meta-heuristic methods for the discrete time–cost trade-off problem (DTCTP), very little success has been achieved in solving large-scale instances. This paper presents a discrete particle swarm optimization (DPSO) to achieve an effective method for the large-scale DTCTP. The proposed DPSO is based on the novel principles for representation, initialization and position-updating of the particles, and brings several benefits for solving the DTCTP, such as an adequate representation of the discrete search space, and enhanced optimization capabilities due to improved quality of the initial swarm. The computational experiment results reveal that the new method outperforms the state-of-the-art methods, both in terms of the solution quality and computation time, especially for medium and large-scale problems. High quality solutions with minor deviations from the global optima are achieved within seconds, for the first time for instances including up to 630 activities. The main contribution of the proposed particle swarm optimization method is that it provides high quality solutions for the time–cost optimization of large size projects within seconds, and enables optimal planning of real-life-size projects.

1. Introduction

In project scheduling, the project duration can be shortened by allocating additional resources to the activities. However, shortening the project durations below their normal levels comes at an additional cost. The objective of time–cost trade-off problem (TCTP) is to identify the set of time–cost alternatives that will provide the optimal schedule under certain conditions. Since in practice many resources (e.g., crews, equipment) are available in discrete units, numerous researches have focused on the discrete version of this problem, called the discrete time–cost trade-off problem (DTCTP).

In the literature, three types of the DTCTP have been included commonly; the cost optimization problem, the duration optimization problem and the Pareto front problem. The objective of the cost optimization problem is to determine the set of time–cost alternatives that will minimize the total cost under certain conditions such as: a given strict project deadline, or a delay penalty. The budget problem aims to identify the time–cost alternatives to minimize the project duration without exceeding a given budget. The Pareto front problem is a multi-objective optimization problem and involves determination of the complete and non-dominated time–cost profile over the set of feasible project durations (Vanhoucke & Debels, 2007) which is called the Pareto front. This paper focuses on the cost optimization problem.

The methods proposed for the DTCTP could be categorized into three areas: exact methods, heuristics, and meta-heuristics. All three types of DTCTP are NP-hard in the strong sense (De, Dunne, Ghosh, & Wells, 1997). Hence, few studies presented exact methods for the DTCTP to solve small and medium scale instances. De, Dunne, Ghosh, and Wells (1995) presented network decomposition/reduction approaches for solving the Pareto front problem. Demeulemeester, Reyck, Foubert, Herroelen, and Vanhoucke (1998) presented a branch and bound algorithm for the Pareto front problem, and solved instances up to 50 activities. Vanhoucke (2005) proposed a branch and bound algorithm for the cost optimization problem considering strict deadlines and time-switch constraints and achieved optimal solutions for instances up to 30 activities. Akkan, Drexl, and Kimms (2005) provided lower and upper bounds for the cost optimization problem with strict deadlines. Hazır, Haouari, and Erel (2010) presented an exact method based on Benders Decomposition for the duration optimization problem, and was able to solve instances including up to 136 activities and 10 modes within 90 min. Szmerekovsky and Venkateshan (2012) studied four integer programming formulations for irregular time–cost trade-offs and achieved optimal solutions for instances with up to 90 activities.

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In an early attempt to achieve an efficient method for solving the TCTP, Siemens (1971) presented a heuristic called the Siemens approximation method (SAM) for the cost optimization problem with strict deadlines, and implemented it on an example including eight activities. Goyal (1975) proposed a modified version of the Siemens approximation method and used the same example with eight activities to demonstrate the modified heuristic. Numerous meta-heuristic solution procedures have been presented in the literature for the DTCTP. Genetic algorithms (GAs) are among the most commonly used meta-heuristics for the DTCTP. Feng, Liu, and Burns (1997) proposed a GA for Pareto front optimization. Hegazy (1999) developed a GA for the cost optimization problem. Zheng, Ng, & Kumaraswamy, 2005 proposed a GA based multiobjective model for the Pareto problem. Kandil and El-Rayes (2006) explored the performance of supercomputing clusters through a GA for Pareto front optimization. Eshtehardian, Afshar, and Abbasnia (2008) presented a GA for Pareto Front optimization of stochastic DTCTP. Fallah-Mehdipour, Bozorg Haddad, Rezapour Tabari, and Mariño (2012) considered a nondominated sorting genetic algorithm along with a multi-objective particle swarm optimization method for Pareto front optimization of DTCTP and time–cost-quality trade-off (TCQTO) problems. Sonmez and Bettemir (2012) developed a hybrid strategy based on GAs, simulated annealing, and quantum simulated annealing techniques for the cost optimization problem. Zheng (2015) presented a GA for the discrete time–cost–environment trade-off problem. Zhang, Zou, and Qi (2015) proposed a GA for the DTCTP in repetitive projects.

Ant colony optimization, shuffled frog leaping, tabu search, Electimize, ε-constraint based evolutionary algorithm, and particle swarm optimization (PSO), are among the meta-heuristic methods proposed for the DTCTP, other than GAs. Afshar, Ziaraty, Kaveh, and Sharifi (2009), Ng and Zhang (2008) and Xiong and Kuang (2008) proposed ant colony optimization algorithms for the Pareto front problem. Elbeltagi, Hegazy, and Grierson (2007) presented a shuffled frog-leaping optimization algorithm for the cost optimization problem. Ashuri and Tavakolan (2015) considered the Pareto front optimization of resources along with the time and cost and presented a shuffled frog leaping algorithm. Vanhoucke and Debels (2007) developed a meta-heuristic approach involving tabu-search and truncated dynamic programming for the three extensions of the cost optimization problem with strict deadlines. Abdel-Raheem and Khalafallah (2011) also focused on the cost optimization problem, and proposed an evolutionary algorithm which simulates the behavior of electrons moving through electric circuit branches. In a recent study, Tavana, Abtahi, and Khalili-Damghani (2014) presented two multi-objective procedures based on ε-constraint method and dynamic self-adaptive evolutionary algorithm for solving the discrete time–cost-quality trade-off problem.

Elbeltagi, Hegazy, and Grierson (2005) and Bettemir (2009) explored the potential of PSO for the cost optimization problem. Yang (2007) and Zhang and Xing (2010) proposed multi-objective PSO algorithms for the Pareto front problem. In a comparison of five evolutionary based algorithms for the cost optimization problem, PSO had the best performance (Elbeltagi et al., 2005). Among eight meta-heuristic methods, including a sole genetic algorithm, four hybrid genetic algorithms, PSO, ant colony optimization, and electromagnetic scatter search, PSO was one of the top performing algorithms along with the hybrid genetic algorithm with quantum simulated annealing for the large-scale cost optimization problem (Bettemir, 2009). Although DTCTP is a discrete optimization problem, to our best knowledge, all of the previous PSO research on DTCTP are restricted in real number space.

The majority of the previous DTCTP research (Abdel-Raheem & Khalafallah, 2011; Afshar et al., 2009; Elbeltagi et al., 2007; Eshtehardian et al., 2008; Fallah-Mehdipour et al., 2012; Feng et al., 1997; Hegazy, 1999; Ng & Zhang, 2008; Xiong & Kuang, 2008; Yang, 2007; Zhang & Xing, 2010; Zheng et al., 2005) used few problem instances including up to eighteen activities to evaluate the performances of the proposed meta-heuristics and did not include the optimal results in comparisons. Even majority of the recent methods was tested with problems including up to twenty activities (Ashuri & Tavakolan, 2015; Zhang et al. 2015; Zheng 2015). Vanhoucke and Debels (2007) included instances up to fifty activities in computational experiments. Tavana et al. (2014) generated instances up to 100 activities for solving the discrete time–cost-quality trade-off problem. Very few studies have focused on optimization of large-scale discrete time–cost trade-off problems. Kandil and El-Rayes (2006) used instances up to 720 activities; however the proposed genetic algorithm required 21 h with a single processor to obtain a Pareto front for a problem including 360 activities. For instances including 630 activities, the best of the eight meta-heuristics tested by Bettemir (2009) was able to achieve solutions with a 2 percent deviation from the optimum in 73 min.

Despite a large amount of the research on the DTCTP has concentrated on designing heuristics and meta-heuristics, very few of the proposed methods can be applied to real-life construction projects which typically include more than 300 activities (Liberatore, Pollack-Johnson, & Smith, 2001). Besides, a few methods that are capable of solving large-scale discrete time–cost trade-off problems usually require a significant amount of computation time to achieve high quality solutions. Hence, for the time–cost trade-off problem there is a significant gap between the literature and real-life project management (Vanhoucke, 2005).

The main objective of this paper is to develop a discrete particle swarm optimization method that is capable of providing high quality solutions for the large-scale discrete time–cost trade-off cost optimization problems within short computational time. The proposed method attempts to improve existing methods for DTCTP by designing a PSO, which can adequately represent the discrete solution space of the DTCTP. A modified version of the Siemens approximation method is integrated to the new discrete PSO (DPSO) to improve the quality of the initial swarm for accelerating the optimization. The paper aims to fill the gap in the literature by presenting a method that can handle the cost optimization problem for real-life-size projects. The remainder of the paper is organized as follows: in Section 2, a mixed-integer formulation is presented for the DTCTP. Section 3 is devoted to the novel discrete particle swarm optimization method. The results of the computational experiments are presented in Section 4, and concluding remarks are made in Section 5.

2. Discrete time–cost trade-off problem

The general discrete time–cost trade-off cost optimization problem in which the objective is to minimize the sum of direct and indirect costs can be formulated as follows (De et al., 1995):

$$\textit{minimize} \quad \sum_{j=1}^{S}\sum_{k=1}^{m(j)}(dc_{jk}x_{jk}) + D \times ic \tag{1}$$

subject to:

$$\sum_{k=1}^{m(j)} x_{jk} = 1, \qquad \forall\, j = \{1, \ldots, S\} \tag{2}$$

$$\sum_{k=1}^{m(j)} d_{jk}x_{jk} + St_j \le St_l, \qquad \forall\, l \in Sc_j \quad \textit{and} \quad \forall\, j = \{1, \ldots, S\} \tag{3}$$

$$D \ge St_{S+1} \tag{4}$$

where dc_{jk} is the direct cost of mode k for activity j; x_{jk} is a 0-1 variable which is 1 if mode k is selected for executing activity