Discrete Firefly Algorithm for Scaffolding Construction Scheduling

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Abstract: Scaffolding activities involve a considerable amount of resource input and effort, particularly in very large scale and complex projects. Based on one of the present research gaps identified from literature review that very limited research emphasis has been placed on the impact of design of time-cost optimization in modular scaffolding construction process, this study aims to formulate a feasible multiobject discrete firefly algorithm (MDFA) for optimizing scaffolding project resource and scheduling schemes. The proposed MDFA has been tested under a scaffolding-specific case and a generic construction project case and manifested that it can produce accurate and effective solutions to assist scaffolding planners in developing practical project schedules and addressing complex time-cost trade-off challenges. **DOI: 10.1061/(ASCE)CP.1943-5487.0000639.**

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Introduction

Low productivity has become one of the prevailing issues in the worldwide construction projects, especially in the complex construction projects such as oil and gas, mining and infrastructure (Wang et al. 2014; Hou et al. 2014). Construction management objectives are generally concerned with the adherence to as-planned resources and schedule. As a temporary and commonly used facility, scaffolding provides a platform for material transfer and sustaining workers working at height. Scaffolding construction, despite less significance against the overall construction activities, indeed involves a considerable amount of resource input and effort, particularly in very large scale and complex projects (Kumar et al. 2013). It is essential on modern construction sites for the erection of new buildings, as well as for modification and maintenance works and are among others used for plant construction, vehicle construction and shipbuilding. Hereby the multiform operation of erection and disassembly of scaffolds is connected with certain levels of productivity and hazards. Therefore, the relationship between careful planning and a coordinated performance in scaffolding is especially important. It is expected that as the growing complexity of industrial projects (Wu et al. 2014a), there is a growing demand of studying the scaffolding activities and associated issues that can on average lead to a very large amount of capital and labor input against the overall project. In addition, one engineering, procurement, and construction management firm found that an investment of scaffolding budget against the total project cost, which at the moment is approximately 12–15%, is no longer sufficient. Scaffolding also has a very decisive impact on determining whether the following construction can stick to the original schedule. In other words, the scaffolding activities are linked with other important activities in terms of the critical path. Therefore, optimization and planning of scaffolding schedule is one of the critical issues to a successful execution of construction work. To address these issues, an effective approach of leveraging resources in scaffolding activities and optimizing the schedules should be produced.

An overview from real project practice shows that erecting scaffolding structures presents critical concerns in terms of health and safety, schedule, and work productivity. Unfortunately, the related research and studies have only looked into very limited fields, for instance, safety accident analysis (Ratay 2004; Rubio-Romero et al. 2013), building information modeling (BIM) supported occupational health and safety design (Kim and Teizer 2014; Taiebat 2011), automated scaffolding design (Kim and Teizer 2014), estimating and planning tool of scaffolding (Kumar et al. 2013), and prediction of the type of scaffolding system (Kim and Fischer 2007). Apart from these, other research studies are more focused on tentatively applying some of the conceptual frameworks to help formulate principles or approaches that might be able to bridge these gaps (Koulinas and Anagnostopoulos 2012; Heon Jun and El-Rayes 2011; Xu et al. 2013; Wu et al. 2014a). Looking into the nontraditional projects, the scaffold components can come in many forms that allow for all types of frameworks to be created depending on the shape and size needed. Those frameworks can be either supported scaffolds (such as independent scaffolds, mobile scaffolds, frame and modular scaffolds) or suspended scaffolds (like single pole scaffolds, multipoint scaffolds, and multilevel scaffolds). Considering the design, shape, and location of the building or other structure it has to be decided which type of scaffold is appropriate. The scaffold system that is most adaptable to the contour of the building or other structure has to be chosen, particularly if a modular scaffold is used. Besides, standardized procedures of instructing the scaffolding practitioners about how to plan and estimate the scaffolding schedules in diversified project scales are still deficient, which leaves a probable

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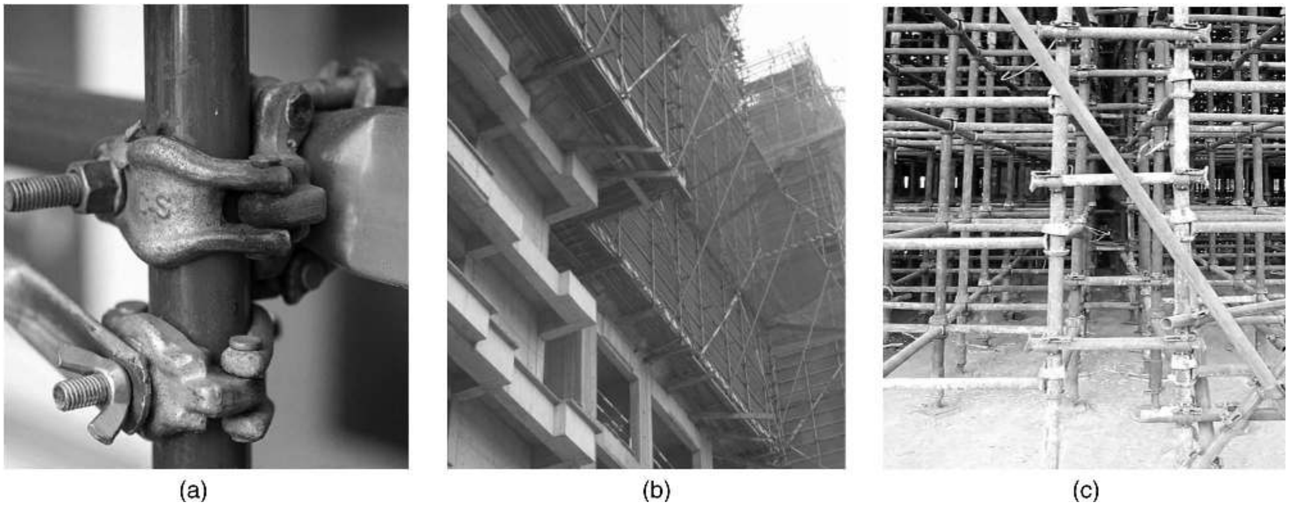

Fig. 1. Number of different scaffolding types (images by Lei Hou): (a) close-up tube and coupler scaffolding; (b) suspended scaffolding; (c) combined scaffolding forms

risk of cost and schedule overruns, as well as an actual need of the project managers to understand scaffolding activities and scheduling issuesfor. With this in mind, this study aims to bridge one of the present research gaps and give the feasible solutions to produce the appropriate project resource and scheduling schemes by formulating a series of unique mathematical models and solving them by the advanced discrete firefly algorithm (FA).

This paper is organized as follows. The literature section states an extensive review of the time-cost optimization approaches and algorithms, followed by a formulated multiobjective mathematical model that based on the existing FA. Real project-based case studies are then presented as a testbed for studying the benefits of using such an improved algorithm, and for the first time, in addressing the real scheduling problem.

Literature Review

On the one hand, because of the huge difference across various scaffolding structures (Fig. 1), time consumed on the processes such as erecting and dismantling could significantly vary. To illustrate, because of the application of premeasured components and quick connection techniques (Rogan et al. 2000), erecting and dismantling a modular scaffolding system could save up to 70% of time as against constructing and decommissioning a traditional scaffolding system that consists of tubes and couplers. Conversely, as compared with the tubular scaffolding, a noticeable advantage of modular scaffolding systems is that it is easy to handle on the site, which can spare workforce, resource, and effort. Notwithstanding, a modular scaffolding system is in general much pricier than a traditional scaffolding system, constructing and decommissioning a modular scaffolding system in countries where workforce plays the most cost-intensive part of the business is not likely to harm the project economy. The genuine downside of the state-of-the-art modular scaffolding systems is the missing adaptability to different shapes of structures (Jackman et al. 2008). By comparison, tube and coupler scaffolds can be connected to form various structure patterns. Besides, frame scaffolding and system scaffolding (two types of the commonly applied modular scaffolding system) are plagued with inconvenience for stock and transport, given the size and weight of the preassembled scaffolding modules.

Still it is recommendable to own a small amount of tubular scaffolding for areas with difficult access possibilities and to tie in with the modular scaffolds; however, there is an overall tendency to use more modular system scaffolding in a global context (Crapo et al. 2008; Viunov 2011). A possible solution to overcome the aforementioned challenges would be making use of lighter materials and designing more flexible structures for modular scaffolding systems. For example, the use of aluminum rather than steel or timber; tailor designing or fabricating varying modular components; or storing scaffolds as close as practical to the work area in order to minimize the distance over which loads are manually moved, clearing access ways for transportation. Also, mechanical aids such as cranes, forklifts or trolleys could be leveraged to handle scaffolds whenever it is possible.

In any construction project, let alone the scaffolding construction, time and cost are always the most critical and intricately concomitant key performance indicators (KPIs). An input of more resources may speed up the progress of construction, but compromise the total cost when adding up the workforce, resources, and machinery expenditure. Because of a limited amount of research studies on selecting options with corresponding time and cost to complete highly productive scaffolding activities, the scaffolding scheduling practice is always confronted with uncertainty and a lack of experience to follow. The emphasis of this study is thus placed on probing into a solution of allocating multiple interrestrained resource types for each modular construction and obtaining optimal time and cost allocation plans. The time-cost trade-off problems (TCTPs) are multiobjective optimization problems (Feng et al. 1997; Wu et al. 2014a). Targeting on the project scheme options under the constraints of both project duration and project cost, TCTPs are to screen out the best fit trade-offs to complete an activity. Given the uncertainty of project implementation, i.e., scheduling randomness and activities fuzziness, Ke and Liu (2010) tested diverse algorithms under a software project context and proved that a hybrid intelligent algorithm adapted from genetic algorithm and random fuzzy simulation can solve the software development costing issues (Huang et al. 2009). To help project planners develop practical project schedules without impacting project quality, Kim et al. (2012) proposed a mixed integer linear programming model that took into account the potential quality loss cost in TCTPs, and evidenced that this model could reduce circa 65% excessive crashing activities in construction project coordination. Resource-constrained scenarios have also been regarded as multimode scheduling problems. Li and Zhang (2013) proposed an ant colony optimization (ACO) approach and manifested that against other metaheuristic methods; this approach is particularly beneficial for real construction project paradigms that are subject to renewable and nonrenewable resource constraints. Scheduling problems are normally concerned with construction in flowshop, such as queries scheduling and makespan, which are one of most difficult nondeterministic polynomial (NP)-complete problems. Allahverdi and Al-Anzi (2006) and Zhang et al. (2007) compared a tabu search (TS) approach with other types of algorithms such as particle swarm optimization (PSO) and earliest due date (EDD) heuristics, and computationally evidenced this approach is in principle more effective and less error prone when addressing the small-job-quantity flowshop assembly problems. With regard to problem solving for continuous optimization problems across a broad range of application areas, a simulated-annealing (SA) algorithm was proposed by Kirkpatrick et al. (1983). According to Varadharajan and Rajendran (2005), SA seeks to obtain more Pareto-optimal and computation-economic solutions in the nondominated multiobjective genetic local search against algorithms such as elitist nondominated genetic (ENG) (Suresh and Mohanasundaram 2006) and gradual priority weighting (GPW) (Chang et al. 2002). Finally, population-based approaches incorporating different approaches for generating and refining schedule populations have emerged in the last 15 years, such as genetic algorithm (GA) or hybrid genetic algorithm (HGA) (Pezzella et al. 2008; Gonalves et al. 2005), ant colony optimisation (ACO) (Merkle et al. 2002), particle swarm optimization (PSO) (Jarboui et al. 2008), differential evolution algorithm (DEA) (Pan et al. 2008), and artificial bee colony (ABC) (Karaboga and Basturk 2007). These population-based algorithms are on average more computationally effective for local optimum search in both continuous and discrete multiobjective scheduling problems, thus gradually taking over the previous algorithms. FA is a relatively new algorithm that was first proposed in year 2010. Since then, numerous research studies have underpinned its advantages in well dealing with a wide range of practical applications over the aforementioned algorithms. The use of FA had satisfactory characteristics in sensitivity, calculation speed, accuracy, convergence, and specificity in the areas of image classification (Senthilnath et al. 2011), disease diagnosis (Horng et al. 2012), multiple traveling route selection (Palit et al. 2011; Jati and Suyanto 2011; Yousif et al. 2011), and so on (Yang and He 2013; Yang 2010; Marichelvam et al. 2014). Kazemzadeh and Azad (2011) and Gandomi et al. (2013) concluded that FA outperformed ABC and PSO in terms of obtaining global optimum results and solving highly nonlinear and multimodal design problems, such as engineering antenna design (Basu and Mahanti 2011; Chatterjee and Mahanti 2012; Zaman and Matin 2012). As previously mentioned, scaffolding construction scheduling is one of the difficult discrete optimization problems because of various uncertainties and varying resource constrains. It might be worth contributing to the knowledge of scheduling optimization by looking into whether an intelligent FA algorithm could address such a problem and what level of effects could be attained. In this regard, the current study establishes a mathematical model for this specific modular scaffolding assembly context, proposes a discrete self-adapted FA that reflects several resource constraints, and demonstrates its robustness in producing effective time-cost recommendations.

Resource-Constrained Scaffolding Scheduling

In a large construction site, scaffolds across areas are of different structures and operated independently. This can incur varied labor productivity of operating different scaffolding types (weight/time). The construction sequence of different scaffolds across different areas is subject to a number of precedent constrains as required, as well as the allowable resources such as available workforce.When building a mathematical model, these factors have to be taken into account. The subsequent section states a multiobjective mathematical model specifically designed for the aforementioned cross area scaffolding scenario, and explains the notations within the model. One of the objective functions of the model pursues the least overall cost of constructing all the scaffolds, while the other ensures the least time consumption and the minimum fluctuation of resource usage to complete scaffolding. In the described scenario, this study supposes that the construction site has been divided into M zones. For zone i, a modular scaffolding is required to be selected from J_i options. For a list of mathematical symbols and variables used in subsequent sections, see "Notation" section.

Decision Variables

The decision variables are x_j^m; y_{jt}^m; S_m; C_m; $j = 1, \ldots, J$; $m = 1, \ldots, M$; and $t = 1, \ldots, T$. The variable x_j^m is introduced to stand for the modular options in different zones, and y_{jt}^m is introduced to show whether modular j is being processed in zone m at time t, i.e.

$$x_j^m = \begin{cases} 1 & \text{if modular option } j \text{ is selected at zone } m \\ 0 & \text{otherwise} \end{cases}$$

$$y_{jt}^m = \begin{cases} 1 & \text{if modular option } j \text{ is selected at zone } m \text{ at time } t \\ 0 & \text{otherwise} \end{cases}$$

the decision variables S_m and C_m are starting time and completing time for the scaffolds at zone m.

Objective Functions

The first objective for scaffolding construction is to minimize project duration

$$F_t = S_{M+1} \quad (1)$$

The second objective is to minimize total project cost. To build different scaffolding in different zones, different cost will be caused. This cost can be calculated as

$$F_c = \sum_j \sum_m c_j^m x_j^m \quad (2)$$

In addition to time and cost, fluctuation of resource usage should also be included. For example, throughout scaffolding process, the numbers of workers at different times should be as close as possible. The resource usage r_{kt} of resource k at time t can be computed as

$$r_{kt} = \sum_j \sum_m r_{jk}^m y_{jt}^m \quad (3)$$

Then, the fluctuation of all resource usage (fluctuations of resource use; in project, it generally means undesirable cyclic of hiring and firing) can be measured by

$$F_v = \sum_k \sum_t \left(r_{kt} - \frac{1}{T} \sum_t r_{kt} \right)^2 \quad (4)$$

Precedence Constraints

In practice, scaffolding in some zones must be completed before scaffolding in other zones. The authors introduce a network $(A,\ V)$ to accomplish this precedence relationship where $A = \{0, 1, \ldots, M+1\}$ and edges V are determined through the precedence relationship. Node 0 and node $M+1$ are two dummy nodes to represent starting and completing. The project period is supposed to be $[0, T]$. To ensure scaffolds built according to the given precedence, the following inequalities should be satisfied:

$$S_j \geq C_i + 1, \quad \forall\ (i, j) \in V \tag{5}$$

$$C_m \geq y_{jt}^m \cdot t, \quad j = 1, \ldots, J, \quad m = 1, \ldots, M, \quad t = 1, \ldots, T \tag{6}$$

Resource Constraints

To build and lift modular scaffolds, many resources are required, such as workforce and cranes. We suppose that K resources are required. Throughout the entire project period $[0, T]$, the availability of resource k is restricted to be between 0 and the upper resource limit U_k, $k = 1, \ldots, K$. Now the limit of the resource can be translated as the following constraint:

$$r_{kt} \leq U_k, \quad k = 1, \ldots, K \tag{7}$$

Intrinsic Variables Constraints

In each zone, only one modular scaffold is selected and built. The summation of the unit time to complete a scaffold in each zone should be exactly as the total time required. Thus, the decision variables should satisfy the following constraints:

$$\sum_m x_j^m = 1, \quad j = 1, \ldots, J \tag{8}$$

$$\sum_t y_{jt}^m = x_j^m t_j^m, \quad j = 1, \ldots, J, \quad m = 1, \ldots, M \tag{9}$$

$$x_j^m \in \{0, 1\}, \quad j = 1, \ldots, J, \quad m = 1, \ldots, M \tag{10}$$

$$y_{jt}^m \in \{0, 1\}, \quad j = 1, \ldots, J, \quad m = 1, \ldots, M, \quad t = 1, \ldots, T \tag{11}$$

$$S_j \geq 0, \qquad C_j \geq 0, \quad j = 1, \ldots, J \tag{12}$$

Problem Statement

To sum up, resource-constrained scaffolding scheduling can be formally stated as the following multiobjective optimization problem

$$\min F_t = S_{M+1}$$

$$\min F_c = \sum_j \sum_m c_j^m x_j^m$$

$$\min F_v = \sum_k \sum_t \left(r_{kt} - \frac{1}{T} \sum_t r_{kt} \right)^2 \tag{13}$$

$$\text{s.t. } S_j \geq C_i + 1, \quad \forall\ (i, j) \in V$$
$$C_m \geq y_{jt}^m \cdot t, \quad j = 1, \ldots, J, \quad m = 1, \ldots, M, \quad t = 1, \ldots, T$$
$$r_{kt} \leq U_k, \quad k = 1, \ldots, K$$
$$\sum_m x_j^m = 1, \quad j = 1, \ldots, J$$
$$\sum_t y_{jt}^m = x_j^m t_j^m, \quad j = 1, \ldots, J, \quad m = 1, \ldots, M$$
$$x_j^m \in \{0, 1\}, \quad j = 1, \ldots, J, \quad m = 1, \ldots, M$$
$$y_{jt}^m \in \{0, 1\}, \quad j = 1, \ldots, J, \quad m = 1, \ldots, M, \quad t = 1, \ldots, T$$
$$S_j \geq 0, \qquad C_j \geq 0, \quad j = 1, \ldots, J$$
$$\min F_v = \sum_k \sum_t \left(r_{kt} - \frac{1}{T} \sum_t r_{kt} \right)^2$$

In the optimization problem in Eq. (13), there are several variables x_j^m, y_{jt}^m, S_m, and C_m. However, the variables can be determined if y_{jt}^m is known. The constraint presented in Eq. (8) ensures that there is exactly one module built at each zone. The constraint presented in Eq. (9) ensures that if modular m is selected at zone j, scaffolding time must equal the corresponding duration. The constraint presented in Eq. (7) ensures that all the used resources at any time are not exceeded their limits. The constraints presented in Eqs. (5) and (2) are precedence constraints. The constraints presented in Eqs. (10)–(12) are binary constraints and non-negative constraints.

Tchebycheff Decomposition

In this section, a Tchebycheff decomposition method is introduced to convert the multiobjective optimization problem presented in Eq. (13) into a number of scalar optimization problems. In the Tchebycheff approach, for the given weights λ_1, λ_2, λ_3, the corresponding scalar optimization problem is defined as

$$\min g^{te} = \max\{\lambda_1|F_t - F_t^*|, \lambda_2|F_c - F_c^*|, \lambda_3|F_v - F_v^*|\} \tag{14}$$

$$\text{s.t. } S_j \geq C_i + 1, \quad \forall\ (i, j) \in V$$
$$C_m \geq y_{jt}^m \cdot t, \quad j = 1, \ldots, J, \quad m = 1, \ldots, M, \quad t = 1, \ldots, T$$
$$r_{kt} \leq U_k, \quad k = 1, \ldots, K$$
$$\sum_m x_j^m = 1, \quad j = 1, \ldots, J$$
$$\sum_t y_{jt}^m = x_j^m t_j^m, \quad j = 1, \ldots, J, \quad m = 1, \ldots, M$$
$$x_j^m \in \{0, 1\}, \quad j = 1, \ldots, J, \quad m = 1, \ldots, M$$
$$y_{jt}^m \in \{0, 1\}, \quad j = 1, \ldots, J, \quad m = 1, \ldots, M, \quad t = 1, \ldots, T$$
$$S_j \geq 0, \qquad C_j \geq 0, \quad j = 1, \ldots, J$$
$$\min g^{te} = \max\{\lambda_1|F_t - F_t^*|, \lambda_2|F_c - F_c^*|, \lambda_3|F_v - F_v^*|\}$$

where $F_t^* = \min\{F_t$: subject to the constraint in Eq. (5)–(12)}; and F_c^* and F_v^* are defined similarly. For each given weight vector $\lambda = [\lambda_1, \lambda_2, \lambda_3]^T$, it can be proven that the corresponding solution of the scalar optimization problem in Eq. (14) is a Pareto optimal solution of the multiobjective optimization problem in Eq. (13). Conversely, it is stated that for any Pareto optimal solution of the constraint in Eq. (13), there exists a weight vector λ so that the Pareto optimal solution of Eq. (13) is also a solution of the corresponding scalar optimization problem in Eq. (14). Therefore, different Pareto optimal solutions can be obtained through varying the weight vector $\lambda = [\lambda_1, \lambda_2, \lambda_3]$.

With $\lambda^1, \ldots, \lambda^N$ being a set of even spread weight factors, the next step is to solve the optimization problem in Eq. (14) for the corresponding λ_i, $i = 1, \ldots, N$. For a given λ_i, addressing the optimization problem in Eq. (14) is by no means effortless if the number of scaffolding zones is large. Conversely, it is noted that for two close weight vectors λ_1 and λ_2, both sides of the objective function in Eq. (14) should be proximal. Based on this observation, the neighborhood search idea proposed by Tahir et al. (2007) will be leveraged to approximate the Pareto front of Eq. (13) through minimizing all the optimization problems in Eq. (14) with $\lambda^1, \ldots, \lambda^N$ being simultaneously processed in a single run.

FA Introduction

FA is a population-based algorithm developed by simulating the social behavior of fireflies. It uses three idealized rules to search an optimal solution: (1) fireflies are attracted by other fireflies in term of their brightness and distance between them; (2) the attractiveness between two firefly colonies is proportionally increased with the increased brightness, and decreased with the Cartesian or Euclidean distance between them; (3) the brightness of a firefly is associated with objectives; and (4) if there is no firefly brighter than the other, that firefly will update.

Individual Representation

As a population-based algorithm, FA is made up of a number of fireflies X_i, $i = 1, \ldots, \text{pop}$, with brightness $B(X_i)$. In a standard FA, the light intensity I of a firefly is inversely proportional to the value of the objective function $I(X) \propto [-\text{objective}(\text{X})]$ for minimum optimization problems, while the light intensity $I(r)$ varies according to the distance as follows:

$$I(r) = I_0 e^{-\gamma r^2} \tag{15}$$

where λ = light absorption coefficient; and I_0 = light intensity of the source. Thus the attractiveness β can be defined as

$$\beta(d) = \beta_0 e^{-\gamma d^2} \tag{16}$$

where β_0 represents the attractiveness of firefly at $d = 0$. The distance d between fireflies i and j is defined as follows:

$$d_{ij} = ||X_i - X_j|| = \sqrt{\sum_{k=1}^{d} (X_{ik} - X_{jk})^2} \tag{17}$$

Movement

The movement of a firefly i attracted to another firefly j with higher brightness is determined by

$$X_i(t+1) = X_i(t) + \beta_0 e^{-\gamma d_{ij}^2}[X_i(t) - X_j(t)] + \alpha\varepsilon \tag{18}$$

where t = iteration number of process; α = randomization parameter generated from interval $[0, 1]$; and ϵ = random number drawn from Gaussian distribution.

The new position of a firefly is determined by three terms: the current position of the firefly, attraction to the other fireflies, and a random walk that consists of a randomization parameter α. The position of fireflies will be updated iteratively until their convergence cater to the optimal solution.

Discrete FA to Optimize Scaffolding Scheduling

Solving the optimization problem in Eq. (14) is infeasible if many scaffolding zones are to be scheduled. In this section, the authors will develop a heuristic method to solve it based on a discrete FA. As described in Zhang et al. (2006), for given scheduling priorities and option modes, multiple activities can be scheduled according to their priorities. Among schedulable activities whose predecessors are all completed and which require no more resources than the available amount at the time, the activities with higher priority will be scheduled earlier than others with lower priorities. Thus, the solution of the problem is equivalent to finding an optimal combination of scheduling priorities and option modes. In the following, the authors will describe how to utilize FA to search an optimal combination of scheduling priorities and option modes.

Solution Representation

The FA was originally developed for continuous optimization problems. To enable it to solve this problem, the position of a firefly needs to be mapped to find a feasible solution of the problem. In this problem, the solution search space is the combination of scheduling priorities and option modes. Let the ith firefly position at the t step be $X_i = [x_{i1}, \ldots, x_{iM}, m_{i1}, \ldots, m_{iM}]^T$. The authors will introduce a map to convert the first M elements $x_{i1}, \ldots, x_{iM}$ into scheduling priorities and the last M elements $m_{i1}, \ldots, m_{iM}$ as the corresponding modes.

As for the first M elements $x_{i1}, \ldots, x_{iM}$, the smallest position value (SPV) rule Marichelvam et al. (2014) will be used to convert the continuous position values to scheduling priorities. More precisely, SPV will sort the values $x_{i1}, \ldots, x_{iM}$ from the smallest to the largest. Then, the corresponding priority will be assigned for each zone according to its order. For example, if there are 7 zones to be scheduled and $[x_{i1}, \ldots, x_{i7}] = [0.15, 0.23, 0.14, 0.76, 0.35, 0.21, 0.42]$. Then, the corresponding scheduling priorities are $[2, 4, 1, 7, 5, 3, 6]$.

For the option modes, the value m_{ij} will be bound to $[1, J_i]$, $i = 1, \ldots, M$, where J_i is the number of options for zone i. In order to convert m_{ij} into the option mode, a rounding operator that rounds m_{ij} to the nearest integer is used. For example, if $m_{ij} = 1.35$, the Option 1 will be used; if $m_{ij} = 2.73$, the Option 3 will be used. In the iteration process, if m_{ij} is lower than 1 or larger than J_i, then it is reset as 1 or J_i to maintain its bound $[1, J_i]$.

Objective Value Computation

In the implementation process, each firefly stands for a combination of scheduling priorities and option modes. To manipulate the movement of these fireflies, it is necessary to evaluate the objective of each firefly in order to approximate the Pareto front of the problem. To compute the objective function, the schedule generation scheme adapted from Kim and Ellis (2010) will be adopted.

The schedule generation scheme is to generate a feasible activity schedule. There are two schedule generation schemes: serial schedule generation scheme, and parallel schedule generation scheme. A serial schedule generation scheme will transform the scheduling priorities for the given option modes into a feasible schedule as activity increases. For the parallel schedule generation scheme, a feasible schedule will be generated as time increases. Here the authors will make use of the serial schedule generation scheme (Kim and Ellis 2010) to generate feasible scheduling. After a feasible schedule is generated through serial schedule generation scheme, its corresponding value (F_t, F_c, F_v) can be computed.

Algorithm Implementation-Discretization

In FA, a firefly moves to a new solution according to the attractiveness from other fireflies with higher brightness. Because the code includes integer vectors, the updating rules in Eq. (18) no longer fit the discrete variables. Thus, they are redefined in discrete form

$$x_i = \mathrm{sig}\left\{\beta_0 e^{-\gamma r_{kl}^2}(X_1 - X_k) + \alpha\left[\mathrm{r\,and}\,(0,1) - \frac{1}{2}\right]\right\} \qquad (19)$$

In Eq. (19), the function $Y = \mathrm{sig}(X)$ is defined as

$$\begin{cases} y_i = 1, & \text{if } r \text{ and } (0,1) < \mathrm{sigmoid}(x_i) \\ y_i = 0, & \text{if } r \text{ and } (0,1) \geq \mathrm{sigmoid}(x_i) \end{cases} \qquad (20)$$

where $Y = \{y_1, y_2, \ldots, y_n\}$, $X = \{x_1, x_2, \ldots, x_n\}$, and the sigmoid function is defined as

$$\mathrm{sigmoid}(x) = \frac{1}{1+e^x} \qquad (21)$$

Real variables such as coordinates and power can update according to formula in Eq. (18). Obviously, the new defined update mechanism is simple and easy to be realized. To promote exploration and exploitation of the algorithm, the randomness coefficient is reduced as the iterations proceed. Given the scale variations of each problem, α_t is assigned as $0.95^t\ \alpha_0$ (α_0 is the initial randomness factor and t is the number of iteration), and the rescaled parameters α_0 and γ are set as follows (Yang 2013):

$$\alpha_0 = 0.01L, \qquad \gamma = 0.5/L^2 \qquad (22)$$

where L = range size between upper and lower bounds of x.

Algorithm Implementation-Framework of the Proposed Approach

The whole framework of the proposed multiple-object discrete firefly algorithm (MDFA) for scaffolding scheduling is given in Fig. 2. First, the algorithm's parameters are initialized. Then, weight vector $\{\lambda_1, \ldots, \lambda_n\}$ is generated to initialize individuals. Because the value range of objective functions of the problem is varying, to avoid the results converge to some certain domain, the rule in Eq. (14) is modified as below:

$$g^{te}(x|w^j, Z) = \max_{1\leq i\leq m}\left\{w_i^j \frac{F_i(x) - \min_i Z}{|\max_i Z - \min_i Z|}\right\} \qquad (23)$$

where $\max_i z$ and $\min_i z$ = maximal and minimal values the ith objective function. Next, the algorithm performs the cycle for updating the individuals simultaneously according to Eq. (23). At each step, the individuals use the schedule generation scheme (SGS) to schedule scaffold. Furthermore, the neighboring individuals will be updated if the new solution dominates them. The cycle is repeated until the iteration satisfies the stopping criterion.

Case Study and Verification

Scaffolding Case Study

In this section, an industrial scaffolding construction operating on Australia North Shore LNG construction site is selected as a case illustration. To prevent the schedule overruns, the initial measures the project team took were primarily to use more productive equipment or hire more workers. Unfortunately, this sacrificed the overall project cost. To address the problem, intricately related variables such as time, cost, and workforce are reconsidered concomitantly as a multiobjective optimization problem during the process of rescheduling the entire project from the project management perspective. The primary objective focuses on selecting options with corresponding time, cost, and workforce to complete an activity so as to concurrently minimize the project duration and/or project cost. From the aforementioned section, a high-level mathematical model is generated for scheduling purpose, and this model is also self-adaptive given the resource constrains. The model specifically applies to the modular construction issues by meticulously analyzing available data resources and concluding deterministic relationships between scaffolds erection, productivity, and other relevant affecting factors. To evaluate and verify the effectiveness of the proposed MDFA, the proposed algorithm has been coded in *Visual C++ 6.0*. The experiments have been conducted on a computer under Windows 7.0 with Intel i5 CPU and 4 GB memory. The population size is set as 66. The neighbor size is 6. The maximum number of iterations is 1,000. Two cases studies are tested and analyzed subsequently.

Scaffolding Case Analysis

An activity network of the project is shown in Fig. 3, with 12 activities shown in order of precedence; the activity data is shown in Table 1. In this case study each activity incorporates a number of unique scaffold modules and for each activity the number of crew, equipment, work hours, and direct costs are presented. In this case, the available resources (number of crews and equipment) are assumed at no larger than 10 for each work hour and the project duration less than 25 days. F_t, F_c, and F_v are the three project optimization objectives as previously mentioned.

Using the optimization model presented in Eq. (13), the presented MDFA was applied to generate the solution to the problem. Where the parameters are preset as: population size is 66 ($M = 3$, $H = 10$), maximal iteration is 1,000, and resource constraints U are set according to Table 1.

The deadline of the project $t^D = 25$ days, so the longest duration is not more than $25 \times 8 = 200$ h. The calculation of payment is based on the standard rate for skilled workers (constant $c = 60/\mathrm{h}$). Normally cost c_{ij} is in direct and inverse ratios to the number of crews, therefore it is set that $c_{ij} = cx_{ij}$. After a run of the proposed algorithm, a quasi-optimal duration and resources allocation of the problem is presented in Table 2 and Fig. 4. Table 2 shows the results from the proposed MDFA after deleting the duplicate solution sets. The optimal solutions for project resources allocated have been produced with the average time consumption, number of workers, and the total cost. The efficiency of the MDFA method reflects the advantage of using the real data in the search course to help and speed up finding optimality. Different from the case of single-objective optimization, the solutions obtained by the multiobjective optimization algorithms consist of multiple distinct solutions that are all Pareto optimal. As shown in Fig. 4, in reducing the time of the project, the cost of project will more likely increase. Likewise, the leveling and cost of the project reveal an adverse relation.

In order to evaluate the effectiveness of the proposed models and algorithm, a state-of-the-art nondominated sorting genetic algorithm II (NSGA-II) proposed by Ghoddousi et al. (2013) was used as a benchmark. Several metrics adapted from Yu and Gen (2010) were applied to assess the accuracy and the diversity of the Pareto front generated by the multiobjective algorithms. The first type is quality metrics (QMs), which represent the percentage of the nondominated solutions in the archive obtained by an algorithm. The second type is generational distance (GD), which is used to

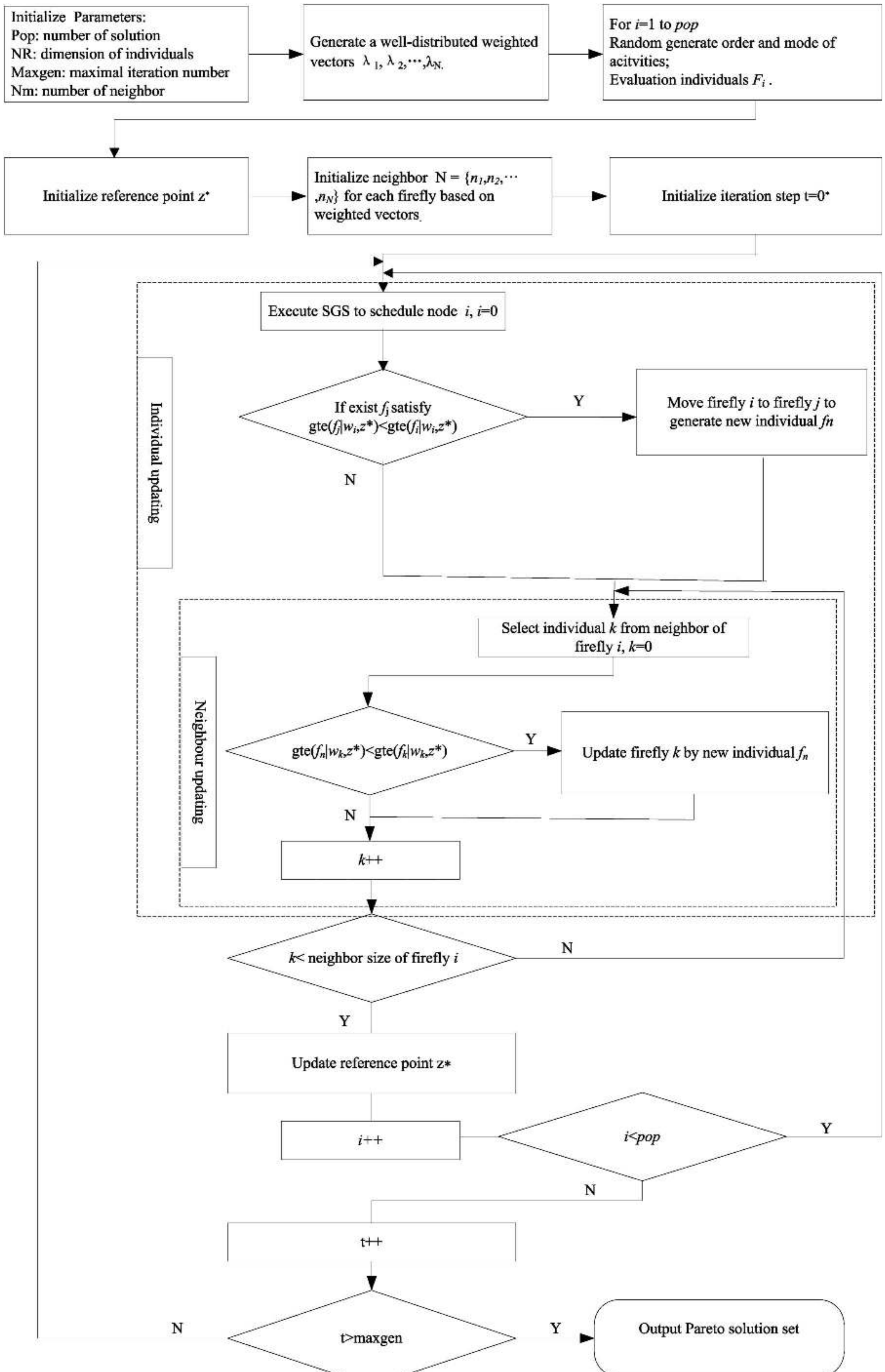

Fig. 2. Framework of discrete FA to optimize scaffolding scheduling

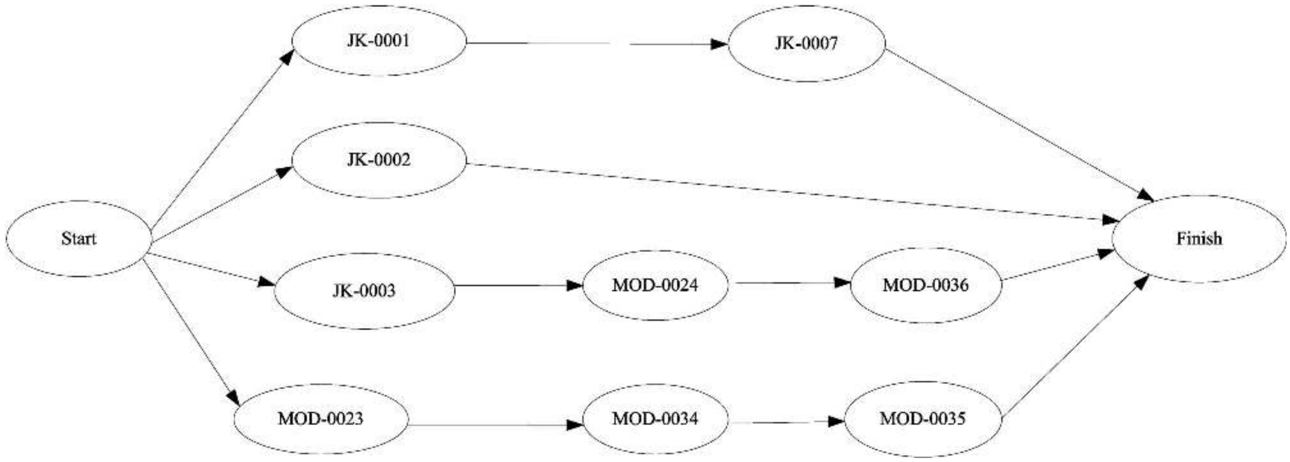

Fig. 3. Activity on node network of project instance

Table 1. Activity Data of the Scaffolding Case Study

Activity	Precedent	Types of scaffold modules	Crews	Number of equipment	Duration (work hours)	Direct cost (\$K)
JK-0001	—	1. Independent tied scaffold	3	1	30	23
		2. Birdcage scaffold	4	1	40	21
		3. Tower scaffold	4	2	40	12
JK-0002	—	1. Independent tied scaffold	4	1	60	21
		2. Birdcage scaffold	1	3	70	80
		3. Tower scaffold	2	1	20	60
		4. Slung scaffolds	4	1	30	50
JK-0003		1. Independent tied scaffold	4	1	30	13
		2. Birdcage scaffold	4	3	50	38
		3. Tower scaffold	1	1	10	40
MOD-0023		1. Independent tied scaffold	4	2	30	33
		2. Birdcage scaffold	4	3	50	20
MOD-0024	JK-0003	1. Independent tied scaffold	3	2	18	12
		2. Birdcage scaffold	1	1	30	24
		3. Tower scaffold	4	1	50	15
		4. Slung scaffolds	3	2	22	11
MOD-0034	MOD-0023	1. Independent tied scaffold	8	4	52	22
		2. Birdcage scaffold	4	2	68	12
		3. Tower scaffold	5	4	58	28
MOD-0035	MOD-0023	1. Independent tied scaffold	7	1	50	18
	MOD-0034	2. Birdcage scaffold	4	5	80	47
		3. Tower scaffold	2	1	15	19
		4. Slung scaffolds	3	5	15	19
MOD-0036	JK-0003	1. Independent tied scaffold	6	1	50	215
	MOD-0024	2. Birdcage scaffold	6	1	60	300
		3. Tower scaffold	1	2	40	90
JK-0007	JK-0001	1. Independent tied scaffold	5	2	60	200
		2. Birdcage scaffold	5	1	58	300
		4. Slung scaffolds	2	2	25	140
JK-0008	—	1. Independent tied scaffold	4	5	45	380
		2. Birdcage scaffold	5	1	60	106
		3. Tower scaffold	5	1	35	100
JK-0009	JK-0008	1. Independent tied scaffold	2	2	45	305
		2. Birdcage scaffold	2	2	20	146
		3. Tower scaffold	1	1	18	150
		4. Slung scaffolds	4	3	17	90
MOD-0041	MOD-0023; MOD-0034; MOD-0035	1. Independent tied scaffold	6	5	21	56
		2. Birdcage scaffold	6	5	66	310

calculate the distance between the Pareto front and the solution set. And the final metrics are spacing metrics (SMs), which are to measure the diversity of solutions in archive. For the sake of unbiased comparison, the benchmarked algorithm NSGA-II also applied 66 individuals as the population scale. The crossover rate was set as 0.8, and the mutation rate was 0.01 for all variables.

Because the true Pareto front was difficult to obtain, this study operated two algorithms and ran 30 trials to generate nondominated

Table 2. Pareto Solutions Achieved by the Proposed MDFA for the Scaffolding Case Study

Solution number	Time (work hours)	Cost (\$K)	Leveling	Solution number	Time (work hours)	Cost (\$K)	Leveling
1	124	746	647.5	2	126	690	449.8
3	133	681	380.9	4	133	680	391.3
5	134	677	330.2	6	134	665	361.9
7	134	660	488	8	139	648	523.8
9	143	647	558	10	144	636	471.8
11	146	708	270.7	12	146	697	281.5
13	146	635	462	14	154	637	383.7
15	154	623	494.7	16	163	635	353.2
17	163	625	402	18	163	623	484.1
19	164	621	604.2	20	166	608	603.3
21	172	621	423.8	22	172	612	437.3
23	173	610	465	24	174	597	514.4
25	182	596	590.8	26	192	591	633.9
27	192	585	780	—	—	—	—

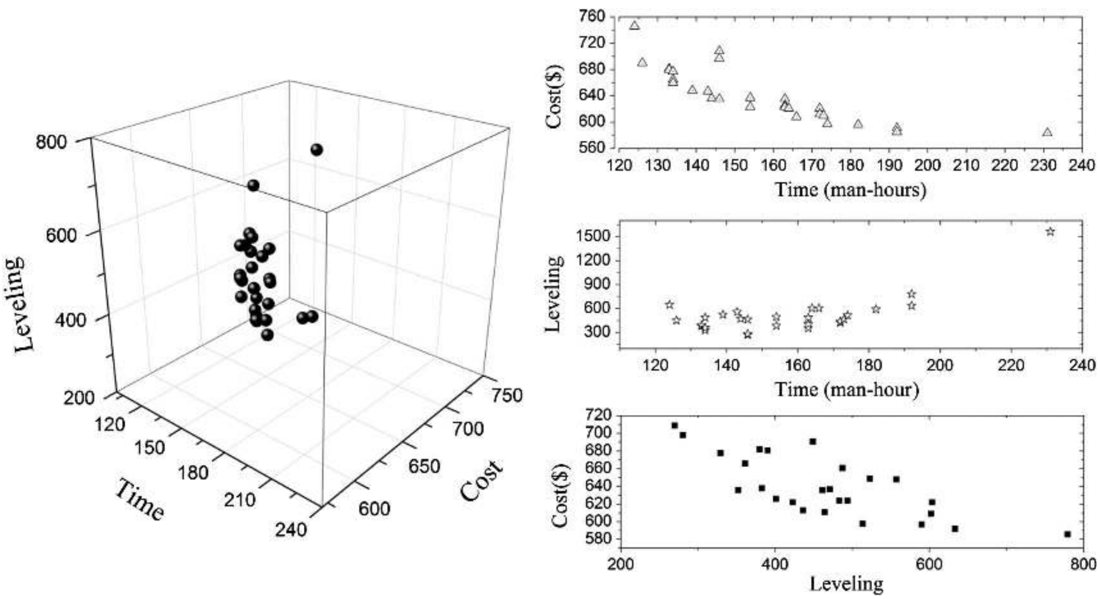

Fig. 4. Pareto front of the scaffolding case study

Table 3. Statistical Results of Three Metrics Based on 30 Independent Runs for the Scaffolding Case

	MOFA			NSGA-II		
Statistic values	GD	SM	QM	GD	SM	QM
Maximum	77.95	89.64	0.169	94.12	45.9	0.1
Minimum	8.89	15.06	0.0116	20.8	9.4	0.007
Mean	38.47	45.5	0.088	55.21	23.17	0.049
Standard deviation	19.76	19.70	0.038	18.81	10.17	0.026

MDFA solutions. The solutions obtained by these trials were gathered and the dominated and closer solutions were deleted. Then 100 solutions were achieved for the Pareto front to evaluate the performance of the algorithms. Furthermore, two algorithms were repeated for 30 independent times for the case study. The statistical values and metrics levels of these trials are shown in Table 3 and Fig. 5.

The previous outcomes reveal that MOFA is superior to NSGA-II in the aspects of the GD and QMs values. It can be inferred that MOFA is capable of obtaining more accurate solutions than NSGA-II. Conversely, NSGA-II is capable of obtaining more uniform distribution solutions than MOFA, as NSGA-II uses the crowd sort method to distribute Pareto solutions.

Next, the convergence of the algorithms was compared. Given the same number of individuals for the two algorithms, the number of function evaluation at each iteration stage across two algorithms is set as identical as well. The average values of the GD metric are calculated based on 20 independent runs in MOFA and NSGA-II, respectively.

The result shown in Fig. 6 indicates that MOFA converges faster than NSGA-II in terms of the number of function evaluations in minimizing a GD, which demonstrates that MOFA could be an efficient and effective algorithm for the case study. As shown in Fig. 4, the proposed MDFA generates various results. Users can select one of them to perform the task as per the resource that is applicable. To assist decision making, an interactive fuzzy decision-making approach is capitalized on to select a compromised solution according to the reference parameters (Malekpour et al. 2013). At first, each objective function of the multiobjective resource-constrained scaffolding scheduling problem can be stated as the following membership function:

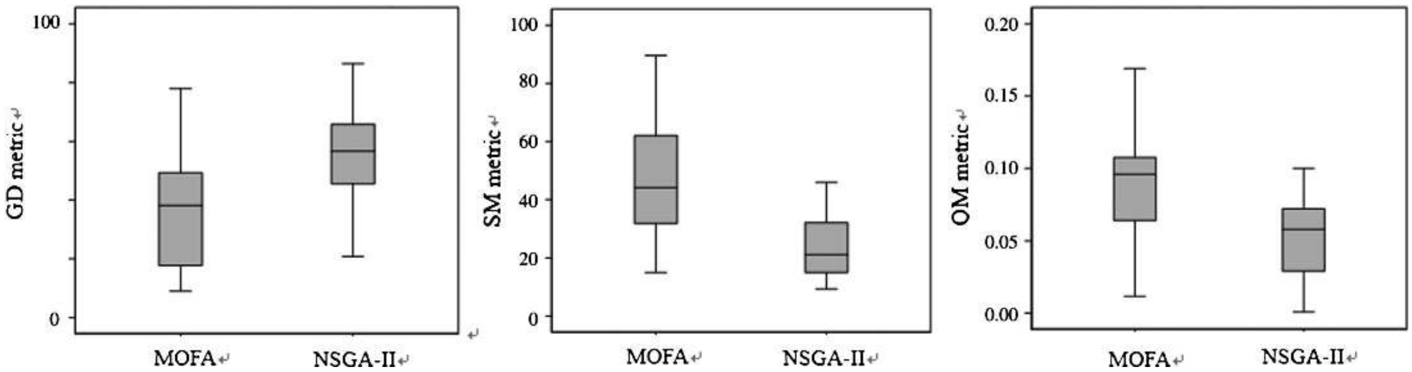

Fig. 5. Metrics levels box plots obtained from MOFA and NSGA-II for the three objectives scaffolding case

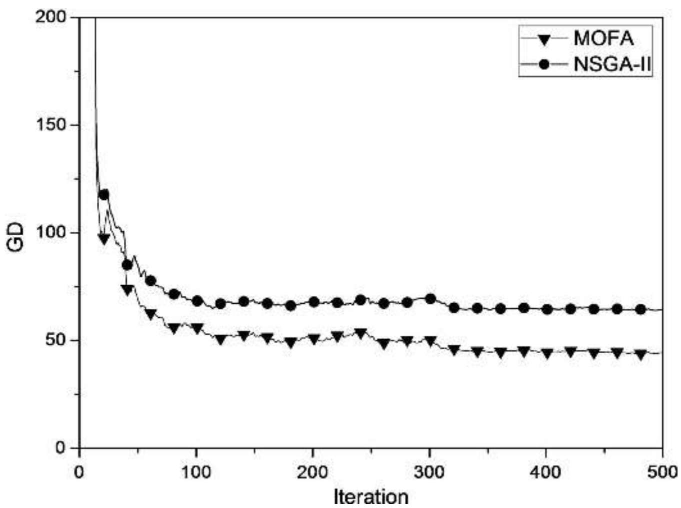

Fig. 6. Evolution of the mean of GD values for scaffolding case in 20 runs

Table 4. Results of Different Compromised Solutions of the Scaffolding Case

Case	Objective 1: time	Objective 2: cost	Objective 3: leveling
Scheme 1	143	647	558.0
Scheme 2	164	621	604.2
Scheme 3	172	621	423.8

$$\omega[f_i(X)] = \begin{cases} 0, & f_i(X) \geq \max f_i, \\ \dfrac{\max f_i - f_i(X)}{\max f_i - \min f_i}, & \min f_i \leq f_i(X) \leq \max f_i \\ 1, & f_i(X) \leq \min f_i \end{cases} \quad (24)$$

where X = solution obtained by MDFA; $\max f_i$ and $\max f_i$ = upper and lower bounds of the objective functions; and $\omega[f_i(\mathrm{X})]$ = degree of the membership of the ith objective functions. According to the membership function, an interactive fuzzy satisfying method can then be used to obtain a comprising solution from the Pareto set. To select a preferred solution, a decision maker can provide the preference level from the membership function between 0 and 1. The preference level is determined through the user expectation of each objective function. Based on the reference value provided by decision maker, a compromised optimal solution based on the reference value of decision maker can be obtained through solving the following problem:

$$D(X) = \min_{X\in\Omega}\{\max|\omega_{ri} - \omega f_i(X)|\}$$

where Ω = set of Pareto front; ω_{ri} = predefined value; and $\omega f_i(X)$ = membership function.

The authors use interactive fuzzy decision to determine a compromise solution from the set of nondomination solutions. The three objectives are time, cost, and leveling. Specifically, time and cost are the most important factors in any resource-constrained scheduling problem. Hence, these objectives are assigned with a high expectation level, with a value ranging from 0.7 to 0.9. Three configuration schemes are proposed to select solutions and the parameters of Schemes 1, 2, and 3 are (0.95, 0.7, 0.5), (0.7, 0.9, 0.5), and (0.5, 0.7, 0.9), respectively. Table 4 illustrates the compromised solutions based on the proposed algorithm.

For example, Figs. 7 and 8 indicate the scheduling results of the Schemes 1 and 3, from which four key elements, namely mode, time, crews, and number of equipment, are respectively shown in detail for each activity of the corresponding scenario. From these charts, it is evident that the project can be finished with a makespan of either 143 or 172 work hours. As a time prior scheduling paradigm considering the resource constraints for each activity, these figures demonstrate the proposed algorithm is capable of furnishing feasible Pareto optimal solutions.

This section leverages a warehouse construction case adapted from Chen and Weng (2009) to validate the proposed models and algorithm. Similar to the scaffolding case, this case also involves a number of activities while each activities incorporates distinct operational modes in terms of operational time, direct cost, demanded resource, and so on. The objective is to obtain well-leveled (nondominated) schedules with respect to these factors. The demanded resource includes one renewable resource, the number of workers (labor), and the upper limit is 12 per day. Based on the proposed MDFA models and algorithm, the optimized results are reflected in Fig. 9, which shows the distribution for 21 nondominated points after the 1000th generation. The relationship between the corresponding nondominated points and the objectives of the model can be interpreted according to the results listed in Table 5. As this is a multiobjective optimization problem, time, cost, and resource leveling need to be analyzed and concluded overall. A reduction in the resource moment deviation means an increase of activity time and additional cost to the project, as evidenced from 22 to 26 consecutive solutions with equal time of 201 work hours, of which smaller resource moments are associated with greater cost values. It is also observed that in accordance with real life, greater cost values are generally derived from smaller resource moment deviations,

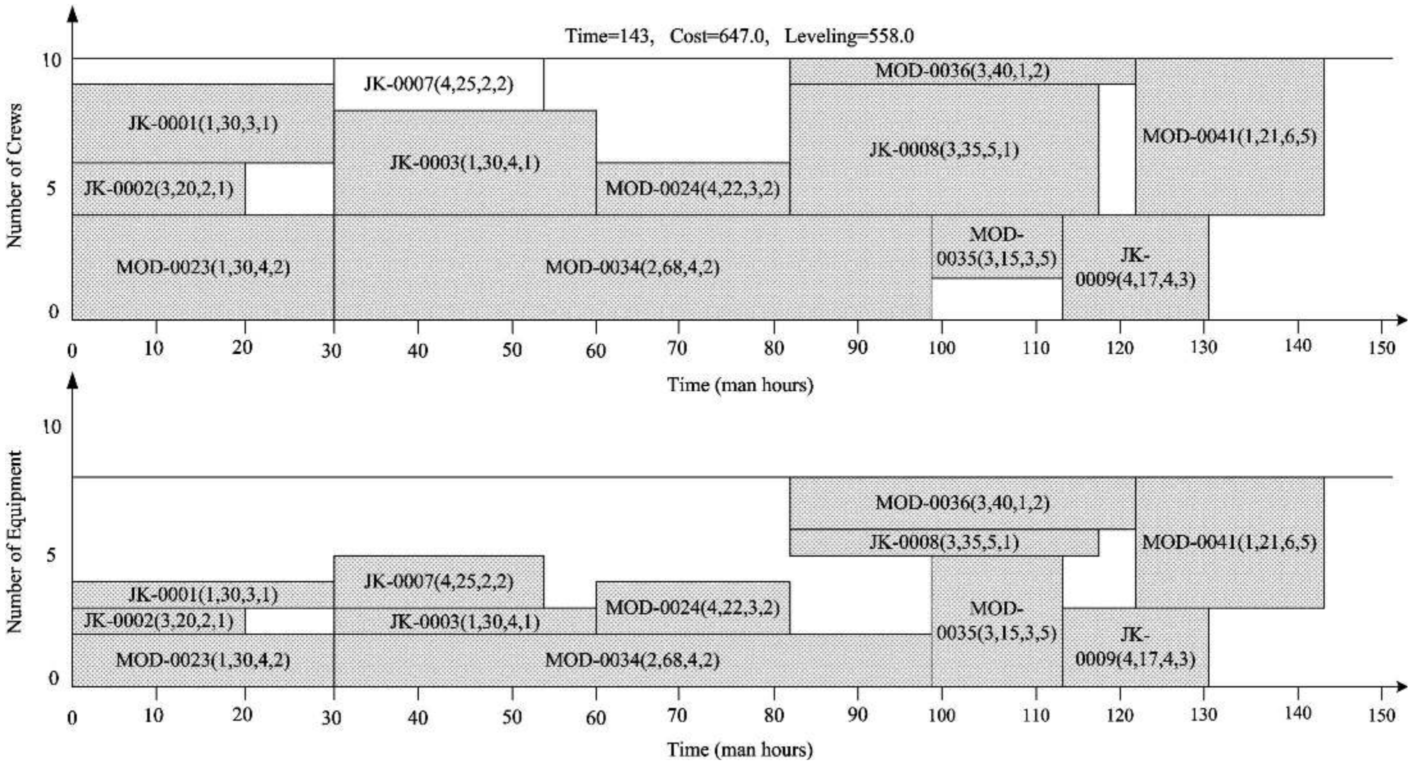

Fig. 7. Timetable of Scheme 1 for the scaffolding case study

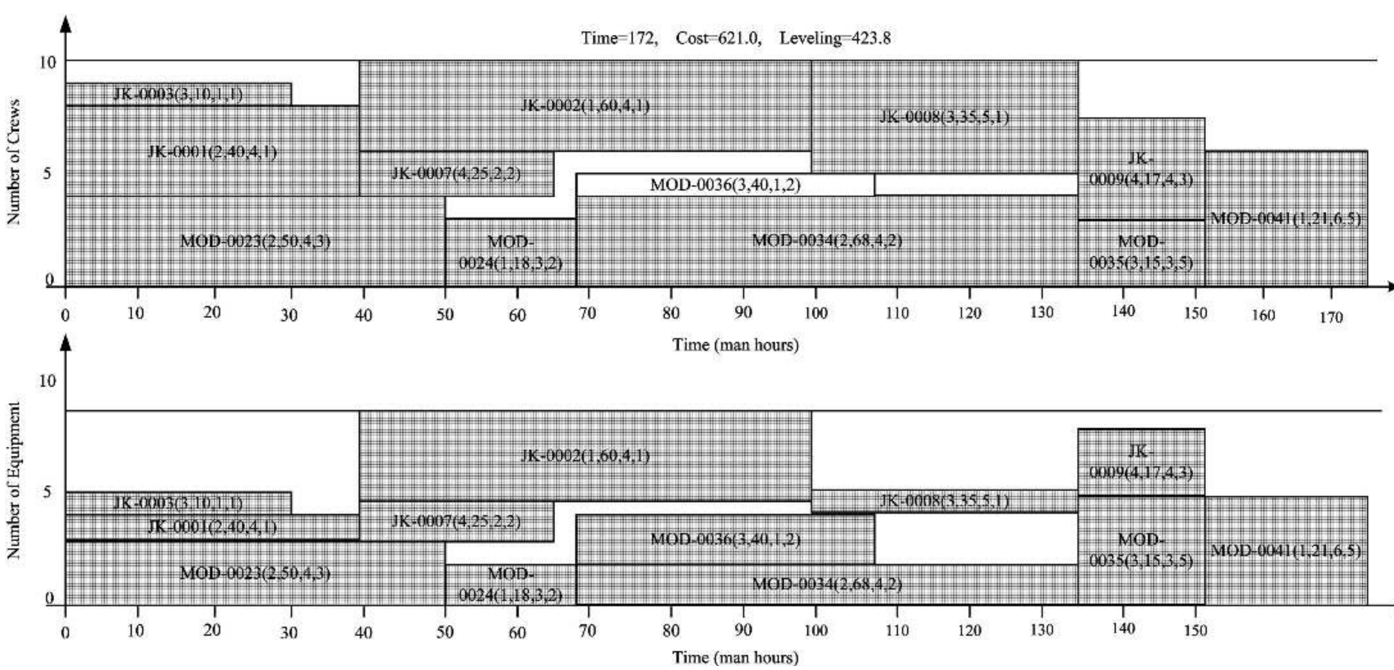

Fig. 8. Timetable of Scheme 3 for the scaffolding case study

which means that the resource leveling can cause fluctuations of the project cost.

In order to evaluate the effectiveness of the proposed models and algorithm in this paper, results were compared against a number of state-of-the-art algorithms generalized by Ghoddousi et al. (2013). Because the true Pareto front is difficult to be attained by a single run, this study ran 10 trials to generate nondominated MDFA solutions. After analyzing all the solutions and eliminating the dominated and similar ones, this paper archives the nondominated results in Table 6.

It can be inferred that the solutions based on the proposed models and algorithm are superior to the counterpart solutions yielded by other algorithms. Specifically, in this case, the proposed approach outperforms the others with a level of 22.2, 53.2, and

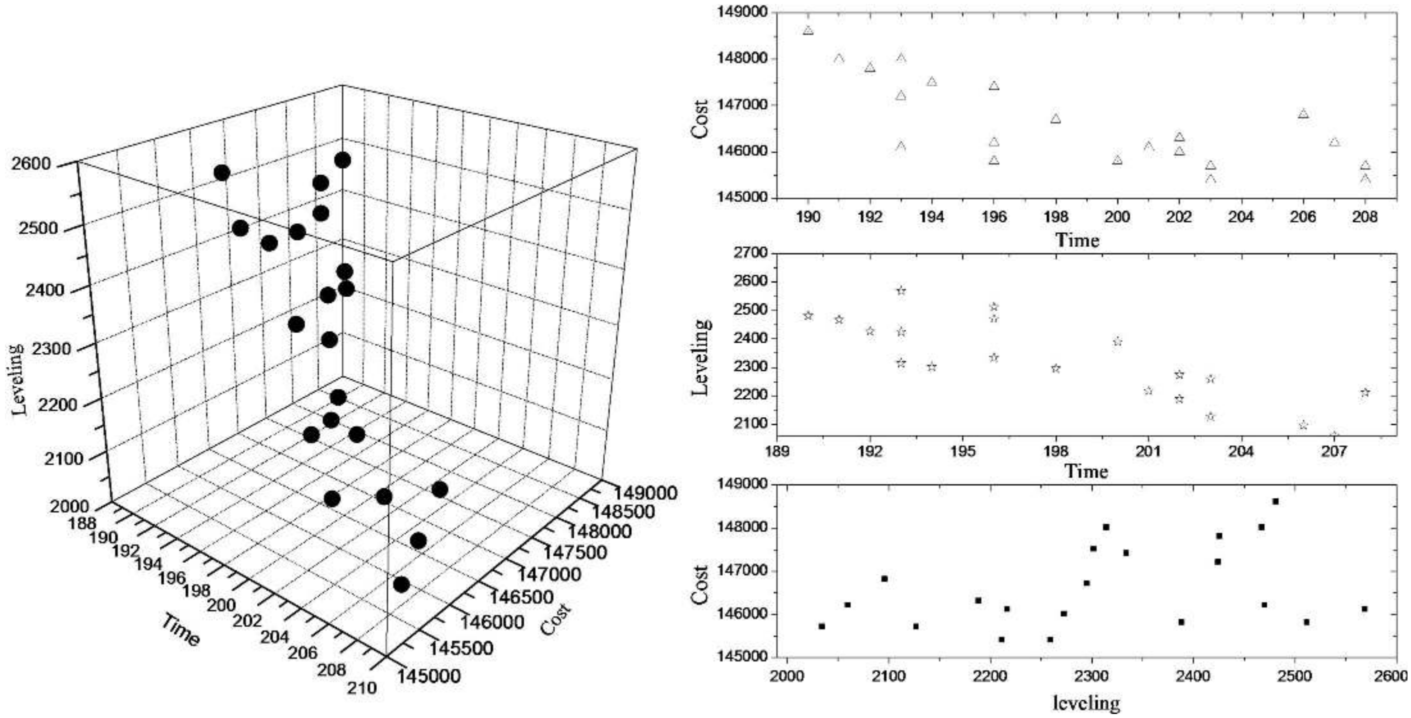

Fig. 9. Pareto front of the construction project case

Table 5. Pareto Solutions Achieved by the Proposed MDFA for the Warehouse Construction Project

Solution	Time	Cost	Resource moment deviation	Solution	Time	Cost	Resource moment deviation
1	190	148,600	2,481.9	2	191	148,000	2,467.9
3	192	147,800	2,426.5	4	193	147,200	2,425.1
5	193	148,000	2,314.8	6	193	146,100	2,569.3
7	194	147,500	2,302.4	8	195	147,500	2,499.9
9	196	148,700	2,427.5	10	196	147,000	2,493
11	196	146,200	2,470.7	12	196	145,800	2,512.3
13	196	147,400	2,334.9	14	197	146,700	2,452.7
15	197	148,100	2,343.2	16	198	146,200	2,442.8
17	198	146,900	2,354.2	18	198	146,200	2,442.8
19	198	147,300	2,334.8	20	198	146,700	2,295.9
21	200	145,800	2,389.2	22	201	147,000	2,249.3
23	201	145,900	2,354.5	24	201	146,300	2,336.4
25	201	146,600	2,267.7	26	201	146,100	2,217.5
27	202	145,400	2,380.1	28	202	146,100	2,294.1
29	202	146,000	2,273.5	30	202	146,300	2,189.1
31	203	145,400	2,259.6	32	203	145,700	2,127.6
33	206	146,800	2,096.7	34	207	146,200	2,060.2
35	208	147,600	2,242.1	36	208	145,700	2,035
37	208	145,400	2,212	38	209	147,100	2,233.7
39	210	148,000	2,141.5	40	210	147,200	2,142
41	210	146,600	2,169.9	42	210	146,200	2,233.7
43	211	146,700	2,107.5	44	211	145,700	2,222.1
45	212	145,400	2,193.8	46	213	146,900	2,081.7
47	213	146,300	2,108.3	48	214	146,400	2,044.6
49	214	145,800	2,102.5	50	217	145,700	2,054.3

Table 6. Comparative Evaluation of the Proposed Method against Other Methods for the Construction Project Case

Approach	QMs	SMs	GD
MDFA	0.11	58.14	17.6
Multiobjective Genetic algorithm (MOGA)	0.09	124.26	96.2

Table 7. Result of Different Compromised Solutions of the Warehouse Construction Project

Case	Objective 1: time	Objective 2: cost	Objective 3: leveling
Scheme 1	194	147,500	2,302.4
Scheme 2	203	145,400	2,259.6
Scheme 3	196	147,400	2,234.9

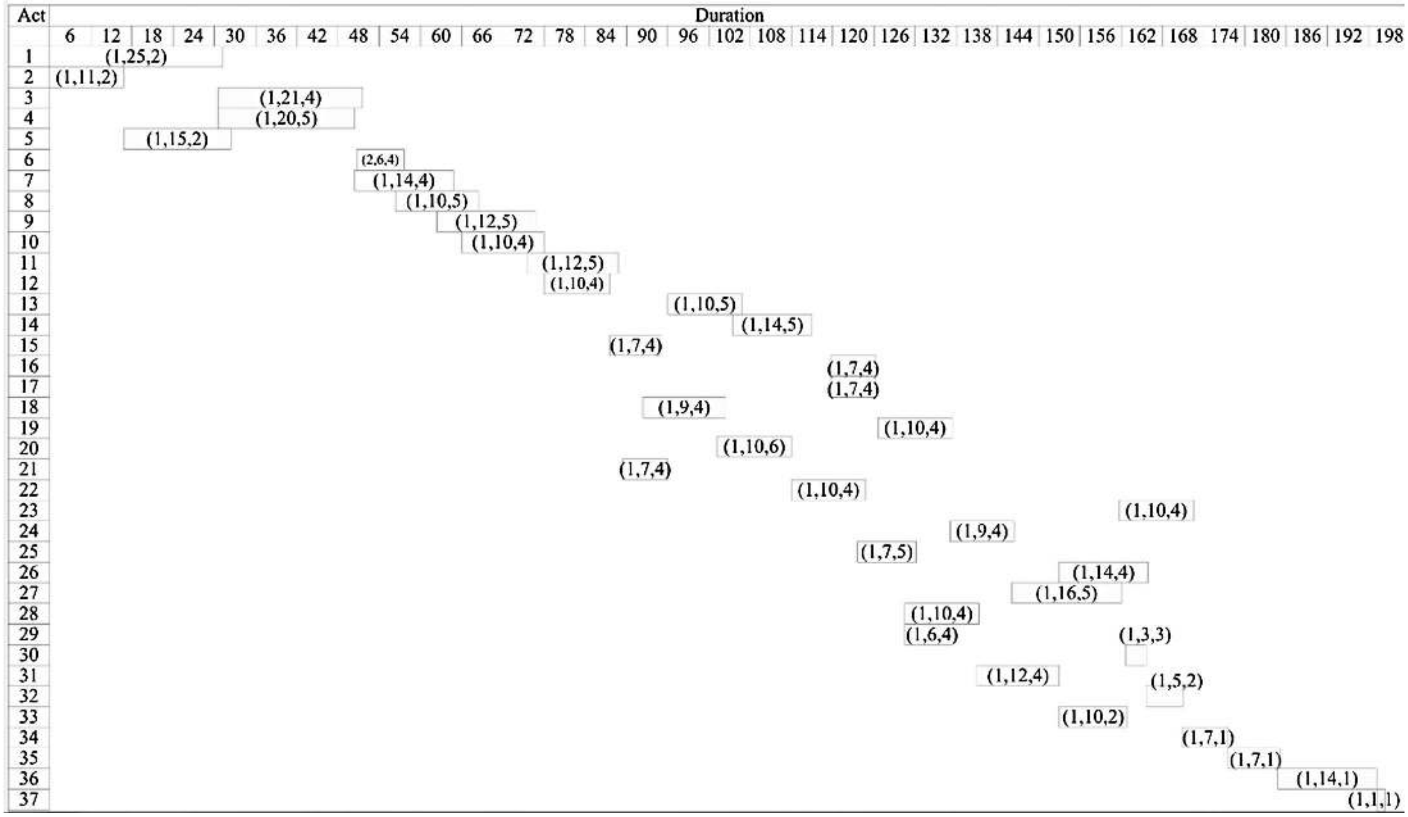

Fig. 10. Optimized timetable for the warehouse construction project under Scheme 1

81.7% in performance of QMs, SMs, and GD, respectively. This study also applies an interactive fuzzy decision approach to determine the compromised solution from a set of nondominated solutions. The configuration parameters (time, cost, and resource leveling) are as follows: Scheme 1 (0.9, 0.5, 0.6); Scheme 2 (0.6, 0.9, 0.5); and Scheme 3 (0.9, 0.5, 0.9). The results of different compromised solutions of the proposed approach are shown in Table 7. Finally, Fig. 10 sets forth the detailed scheduling activities for Scheme 1, from which a feasible Pareto optimal solution (constraints are overcome at each stage) is noticeably demonstrated. This renders the MDFA models and algorithm a feasible tool for the scaffolding project decision makers, and allows them to carry out multiobjective trade-off analysis (time, cost, and resource leveling) and make optimal decisions for their project.

Discussion

The paper studies the multiobjective project scheduling problem in a modular scaffolding construction context. To address the proposed resource-constraint challenges simultaneously (to seek for the optimal Pareto solutions), a MDFA was derived from a multiobjective constrained optimization model that targets the optimal combination of the project makespan (start time, finish time) and execution mode of each project activity. Based on a real scaffolding project, the optimization results manifest the credibility of the proposed models and algorithm when seeking the best workforce trade-off results reflected from time, cost, and resource leveling. The results also reveal that a less fluctuated resource usage would increase project cost, which is consistent with reality. A case study adopted from Chen and Weng (2009) and a number of comparative techniques have been used to verify the accuracy and effectiveness of the proposed models and algorithm, as against the other state-of-the-art algorithms in the nondominated optimization discipline. Because the proposed MDFA is a heuristic and swarm-based algorithm, it can only produce an approximation of the real solution. In the future, testing the proposed MDFA under more complex and varied types of resource constrains is imperative. Lastly, by embedding a resource leveling algorithm module and a Ceil function, the current algorithm will become self-adaptive and applicable for a wider set of discrete problems.

Acknowledgments

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Notation

The following symbols are used in this paper:

C_j = complete time of scaffolding at zone j;
c_j^m = cost of scaffolding at zone j with alternative m;
j = scaffolding zones;
k = resource type;
m = alternatives of modular scaffolding;
r_{jk}^m = required amount of resource k for scaffolding j at zone m;
r_{kt} = resource usage of resource k at time t;

S_j = starting time of scaffolding at zone j;
t = time period;
t_j^m = duration of scaffolding at zone j with alternative m; and
U_k = available upper bound for resource k.

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