Computing (2019) 101:547–570
https://doi.org/10.1007/s00607-018-00693-1

Multi-objective multi-mode resource constrained project scheduling problem using Pareto-based algorithms

Erfan Babaee Tirkolaee[1,2] · Alireza Goli[3] · Milad Hematian[1] · Arun Kumar Sangaiah[4] · Tao Han[5]

Received: 24 October 2018 / Accepted: 21 December 2018 / Published online: 7 January 2019

Abstract
This study addresses the multi-objective multi-mode resource-constrained project scheduling problem with payment planning where the activities can be done through one of the possible modes and the objectives are to maximize the net present value and minimize the completion time concurrently. Moreover, renewable resources including manpower, machinery, and equipment as well as non-renewable ones such as consumable resources and budget are considered to make the model closer to the real-world. To this end, a non-linear programming model is proposed to formulate the problem based on the suggested assumptions. To validate the model, several random instances are designed and solved by GAMS-BARON solver applying the ε-constraint method. For the high NP-hardness of the problem, we develop two metaheuristics of non-dominated sorting genetic algorithm II and multi-objective simulated annealing algorithm to solve the problem. Finally, the performances of the proposed solution techniques are evaluated using some well-known efficient criteria.

Keywords Multi-mode resource-constrained project scheduling problem · NPV · Payment planning · ε-Constraint method · NSGA-II · MOSA

Mathematics Subject Classification 90Cxx · 90-08 · 68Txx · 90B35 · 90B50

1 Introduction

Resource investment is one of the most important issues in the resource-constrained project scheduling problem (RCPSP) which tries to reduce the resource employment costs of a project. In other words, many project activities are allowed to have a delay and in this situation, completion costs of projects, as well as the level of investment in

✉ Tao Han
hant@dgut.edu.cn

Extended author information available on the last page of the article

resources, are targeted in the planning stage before starting the project. So decision-makers seek to create a desired balance between time and cost in projects. For example, in capabilities planning project of military industries with the aims of achieving defined military capabilities according to the investment constraints, optimizing the amount of resources invested in the project with respect to the two factors of time and cost is very critical [4].

In RCPSP, minimization of the cost related resource is done by determining the desirable level of resources required for project activities, mainly at the planning stage. In resource investment, considering the resources needed to carry out activities as well as the precedence relationships, the desired level of access to resources is considered as a decision variable and all activities are scheduled according to determined levels. The resource investment problem was originally introduced by Möhring [30]. He tried to minimize required resources cost while considering the due date of projects. According to Möhring [30], project scheduling problem (PSP) is divided into two categories with respect to the completion time and available resources:

(1) RCPSP: the access level to all kinds of resources is constrained and the goal is to achieve the shortest possible completion time of the project.
(2) Time-constrained project scheduling problem (TCPSP): the total time available to complete the project is constrained and the goal is to determine the optimal level of resources and minimize the utilization cost of resources, assuming that the required resources are unlimited.

The first category is studied in this research with a wide range of applications in the real world. In other words, RCPSP is the most comprehensive subject of scheduling problems which even includes job shop, flow shop and open shop scheduling problems. Generally, RCPSP seeks to find a suitable sequence for performing the activities of a project in such a way that the precedence relationships of the project network and different types of resource constraints on the project are satisfied simultaneously. All of these limitations are in line with a particular measure like time or cost which should be optimized.

RCPSP is one of the problems with rich literature in the field of project management. So far numerous articles and books have been published due to two main reasons. Firstly, this problem is various in terms of the objective function, the characteristics of the activities, resources and precedence relationships, according to practical and industrial conditions and secondly, due to the NP-hardness of these problems, researchers have always sought to develop more efficient solution techniques. Some of the most applicable fields of the project scheduling is product design [8], software design and engineering [7, 29], military capability planning [4, 48] as well as research and development projects for goods and services [13].

Normally, the duration of an activity is fixed and cannot be changed, but in some cases, this time is changeable by incurring additional costs. In fact, the duration of the project activities depends on its importance for the project manager where it can be reduced by considering more expenses. In the multi-mode RCPSP (MMRCPSP), there are a set of acceptable execution modes for each activity such that each one has its own specific and unique duration and consumption level of resources [39]. The time and cost of performing each activity are characterized by the selection of its execution modes [19]. The aim is to determine the optimal execution mode and the start time of each activity to minimize the total completion time of the project. Brucker et al. [5] proved that if the number of non-renewable resources and execution modes of each activity is more than two, MMRCPSP is an NP-Complete problem.

Project management utilizes the knowledge, skills, tools, and techniques required to manage the execution of activities in order to meet the requirements and expectations of the project managers. It employs three powerful tools including required data collection, project planning and project scheduling [38].

In the same vein, another important issue is the project payment planning (PPP), which determines the time and the amount of payment flows and can be done through one of the four existing models [45]:

- Lump-Sum Payment (LSP): the total cost is paid to the contractor when the project is successfully completed.
- Payments at Event Occurrence (PEO): the payments are made during the occurrence of the events.
- Payments at activities' completion times (PAC): the payments are made when each activity is finished.
- Progress Payments (PP): the payments are made at regular intervals and the last payment is made at the completion of the project.

In this research, a bi-objective MMRCPSP with discounted cash flows and PEO-based payments is studied, which is an extension of the research done by He et al. [19]. In the proposed problem, renewable resources (including manpower, machinery, and equipment), as well as non-renewable resources (including consumption and money), are also taken into account to be assigned to the activities during the project. The aim of considering the discounted cash flow is to calculate and maximize the NPV of the project. Moreover, the second objective is to minimize the completion time of the project based on the occurrence of the last event. In other words, the main goals are to determine and allocate the amount of payments and to schedule the activities considering the appropriate execution modes with respect to the time–cost trade-off. To validate the proposed model, the ε-constraint method is applied to cope with the bi-objectiveness of the model, then it is implemented by CPLEX solver of GAMS software. Furthermore, two efficient Pareto-based metaheuristics including non-dominated sorting genetic algorithm II (NSGA-II) and multi-objective simulated annealing (MOSA) algorithm are developed to solve the problem approximately.

The remaining sections of the paper are organized as follows. Section 2 represents the literature review of the research, then the proposed problem and mathematical model are described in Sect. 3. Section 4 introduces the applied ε-constraint method, NSGA-II and MOSA, and the computational results are presented in Sect. 5. Finally, the conclusions and outlook of the research are described in Sect. 6. Moreover, the proposed flow graph of the research is shown in Fig. 1.

2 Literature review

The objective of this section is to investigate the shortcomings of the studies on RSP-SPs. During the last decades, RCPSP was widely investigated by researchers [20, 23].

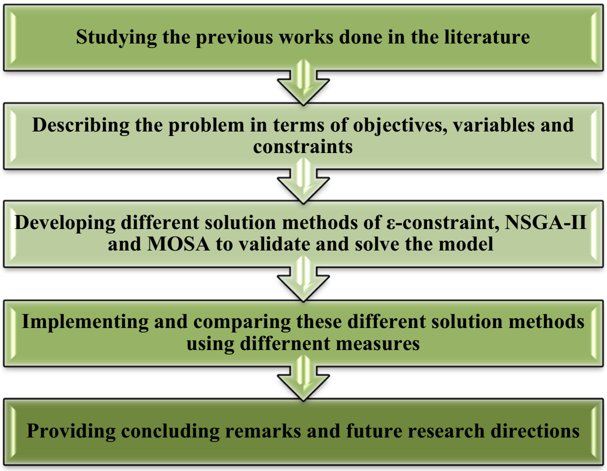


Fig. 1 The proposed flow graph of the research

Although the main focus is on the minimization of completion time of project [17] while some other objective functions implicate on maximizing the net present value (NPV) of the project [19].

Since the discussion of cash flows in PSP was introduced by Russell [36], the problem of scheduling the activities of a project aimed at maximizing the NPV has attracted much attention in the literature. The efforts of many research works have led to the examination of models and methods for solving a large variety, along with the representation of critical path method (CPM), cash payment patterns, resource constraints, and time–cost exchanges. In the context of a review on the PSPs with regard to PPP with the aim of maximizing NPV, the studies conducted by Icmeli and Erenguc [22], Özdamar et al. [34] and Hartmann and Briskorn [17] can be referred.

Dayanand and Padman [9] presented several deterministic models for maximizing contractor's NPV where the delivery time and the amount of pre-determined payments are determined for the project. In the next study, they determined a set of payments regarding the scheduling, and then, in the second step, re-scheduled them to improve the NPV [10]. Szmerekovsky [41] presented a Branch and Bound (B&B) method to solve the project payment scheduling problem (PPSP), which provides the scheduling of the project's payments on the customer request, and the contractor can defend his interests by selecting activities scheduling and rejecting payment schedules.

Ulusoy and Cebelli [44] developed a genetic algorithm (GA) to solve the PPSP considering a timely payment plan that provides the benefits of both customer and contractor. He and Xu [18] examined the effect of the incentive-fining policy on the payment schedules and found that the existence of such a structure would improve the flexibility of a payment schedule. He et al. [19] developed two metaheuristics of simulated annealing (SA) algorithm and Tabu Search (TS) algorithm for multi-mode PPSP (MMPPSP) and examined their performance by generating and solving random samples.

On the other hand, other problems were studied as capital-constrained PSP (CCPPSP). A number of studies have been done on CCPPSP by Özdamar and Dündar

[33], Ulusoy et al. [45], Mika et al. [28], and many others who examined the CCPPSP problem in a single-mode and multi-mode context. Chen and Zhang [6] examined the RCPSP to maximize the NPV of the project under uncertain conditions. They considered random stochastic time and cost for each activity and solved the problem using ant colony optimization (ACO) algorithm.

Aboutalebi et al. [1] presented a bi-objective mathematical model to solve a multi-mode resource-constrained project scheduling problem with discounted cash flows (MMRCPSP-DCF) with the objectives of minimizing the completion time and maximizing the NPV of projects. They applied NSGA-II and a multi-objective particle swarm optimization (MOPSO) algorithm to solve the proposed problem. Hosseini et al. [21] presented a mathematical model to solve MMRCPSP with positive and negative cash flows aimed at maximizing the NPV of the project. They designed an efficient GA to solve the problem.

Leyman and Vanhoucke [26] presented a single-objective model for MMRCPSP with renewable and non-renewable resources and positive and negative cash flows to minimize the NPV of the project. They studied three different payments of PAC, PEO and PP and applied a GA to solve the problem. Sebt et al. [37] proposed a hybrid meta-heuristic algorithm including GA and particle swarm optimization (PSO) algorithm to solve MMRCPSP with the aim of the completion time minimization. Geiger [15] developed an iterated variable neighborhood search (IVNS) to solve a multi-project, multi-mode resource-constrained project scheduling problem (MPMMRCPSP). They tested the performance of their proposed algorithm on some benchmark instances.

Oztemel and Selam [35] designed a bee colony optimization (BCO) algorithm for MMRCPSP in a molding industry. They demonstrated that their proposed algorithm could generate suitable schedules for the projects with a high number of activities and limited resources.

Nabipoor Afruzi et al. [31] studied a robust multi-project resource-constrained scheduling problem (MPRCSP) with uncertainty in activity duration. The main goal of this study was to maximize the total weighted tardiness of the projects. Küçüksayacıgil and Ulusoy [25] studied a bi-objective MPMMRCPSP. Their proposed objectives were to minimize the completion time of projects and the mean of the flow times for individual projects as well as maximizing the NPV of all projects. They implemented a hybrid GA to solve the problem.

In Table 1, briefly, important studies are presented, taking into account the payment method and modeling according to the objective functions.

According to the literature review, the main contributions are described as follows:

- Developing a novel bi-objective mathematical model to consider the two practical objectives of NPV maximization and completion time minimization which is the extension of the proposed model by He et al. [19],
- Integrating the decisions of optimal allocation of payments to the events, optimal modes of activities, calculation of the income and expenses of the project on each event,
- Considering the real-world conditions of activities demand for renewable and non-renewable resources and possible multi-mode of activities which leads to the time and cost trade-off,

Table 1 Literature overview

References	Resources			Payment models				Objective function		Solution method
	Renewable	Non-renewable	Budget	PAC	PP	PEO	LSP	Duration	NPV	
Ulusoy and Cebelli [44]	*	*				*			*	A double-loop GA
Mika et al. [28]	*	*	*	*	*	*	*		*	SA + TS
Seifi and Tavakkoli-Moghaddam [38]	*	*		*	*	*		*	*	SA
Chen and Zhang [6]	*	*				*			*	Ant colony system (ACS) based approach
Aboutalebi et al. [1]	*			*				*	*	NSGA-II + MOPSO
Hosseini et al. [21]	*	*					*		*	Non-dominated Ranking Genetic Algorithm (NRGA) + NSGA-II
Leyman and Vanhoucke [26]	*	*		*	*	*			*	GA
Sebt et al. [37]	*	*						*		Hybrid GA
Geiger [15]	*	*						*		IVNS
Oztemel and Selam [35]	*	*						*		BCO
Nabipoor Afruzi et al. [31]	*							*		A scenario-relaxation algorithm
Küçüksayacıgil and Ulusoy [25]	*	*						*	*	Hybrid GA
The current study	*	*	*			*		*	*	NSGA-II + MOSA

- Developing three efficient solution techniques the of ε-constraint method, NSGA-II and MOSA,
- Applying different comparing measures to test the performance of the solution methods.

3 Problem definition

Assume that there are several activities which have several required resources and several execution modes that each mode has a specific duration, cost and the amount of the required resources. The objectives of the proposed problem are to maximize the NPV and minimize the completion time of the project concurrently. The main questions of the problem are:

1. When and how much payment should be assigned to each event?
2. Which execution mode should be considered for each activity?
3. When is each event completed?
4. How much is the cost of each event?
5. How much is the income of each event?

Consider a project that its contractor's initial capital is equal to ICA. Duration, cost, and demand of activity i for rth resource under mode j are defined by dur_{ij}, $\cos t_{ij}$, dem_{ijr}, respectively, where $i = 1, 2, \ldots, n$; $r = 1, 2, \ldots, R$ and $j = 1, 2, \ldots, J$. The available resources are also defined as a_r that can be either renewable or non-renewable. The cost of each event m ($m = 1, 2, \ldots, M$) is defined as follows:

$$e_m = \sum_{i \in S_m^{start}} \left[\zeta_i \sum_{j=1}^{J} \text{cost}_{ij} y_{ij} \right] + \sum_{i \in S_m^{end}} \left[(1 - \zeta_i) \sum_{j=1}^{J} \text{cost}_{ij} y_{ij} \right] \tag{1}$$

where S_m^{start} is the set of activities starting from mth event, S_m^{end} is the set of activities that end at event m and ζ_i $(0 \leq \zeta_i \leq 1)$ is the cost ratio distribution of the ith activity during its execution. The income amount of event m is calculated by $v_m = \sum_{i \in S_m^{end}} w_i$, where w_i is amount of the gained income from activity i. The final payment is done at the last event of the project which is $p_K = U - \sum_{k=1}^{K-1} p_k$. Here, U, D and α are the contract cost, the considered completion time of the project and the return rate for each period, respectively where $U = \sum_{i=1}^{n} w_i$.

To describe the proposed network of the project, activity on arc (AOA) network is employed so that arcs show the activities and nodes represent the events. The suggested example is depicted in Fig. 2.

3.1 Mathematical model

Indices and sets

i	Index of activities
j	Index of activity modes

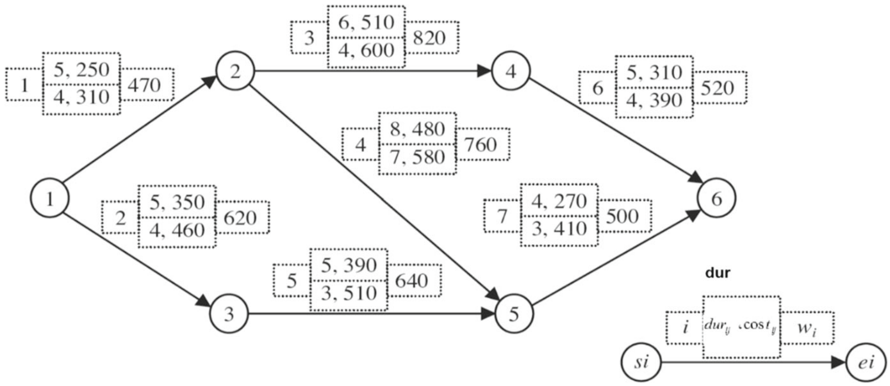


Fig. 2 General scheme of proposed AOA network [19]

k	Index of payments
m	Index of events
r	Index of resources
t	Index of time period
I	Set of activities
J	Set of activity modes
M	Set of events
R	Set of resources including renewable and non-renewable
K	Set of payments
T	Set of time periods
S_m^{start}	Set of activities that begin at event m
S_m^{end}	Set of activities that end at event m

Parameters

ICA	Initial capital of the contractor amount
dur_{ij}	Duration of activity i under mode j
$\cos t_{ij}$	Execution cost of activity i under mode j
dem_{ijr}	Demand of activity i for resource r under mode j
a_r	Available amount of resource r
E_m	Earliest occurrence time of event m
L_m	Latest occurrence time of event m
ζ_i	Cost distribution ratio of activity i during the start and end of the activities
w_i	Income amount of activity i
U	Contract price of the project
D	Project delivery time
α	Rate of return in each period

Decision variables

x_{km}	Binary variable; it is equal to 1 if payment k is assigned to event m, otherwise, it is 0
y_{ij}	Binary variable; it is equal to 1 if activity i is done in mode j, otherwise, it is 0

z_{mt} Binary variable; it is equal to 1 if the event m is completed in period t is equal to 1, otherwise, it is 0

e_m Cost of event m

v_m Income of event m

p_k Amount of payment k

Now, the proposed bi-objective model for our MMRCPSP-DCF is defined as follows:

$$\text{Maximize NPV} = \sum_{k=1}^{K}\left\{p_k \sum_{m=1}^{M}\left[x_{km}\sum_{t=E_m}^{L_m}(\exp(-\alpha t)z_{mt})\right]\right\} - \sum_{m=1}^{M}\left\{e_m \sum_{t=E_m}^{L_m}(\exp(-\alpha t)z_{mt})\right\} \tag{2}$$

$$\text{Minimize makespan} = \sum_{t=E_M}^{L_M} t.z_{Mt}$$

subject to (3)

$$\sum_{m=1}^{M-1} x_{km} = 1 \quad k = 1, 2, \ldots, K-1 \tag{4}$$

$$x_{KM} = 1 \tag{5}$$

$$\sum_{k=1}^{K} x_{km} \le 1 \quad m = 1, 2, \ldots, M \tag{6}$$

$$e_m = \sum_{i \in S_m^{start}}\left[\zeta_i \sum_{j=1}^{J}\text{cost}_{ij}y_{ij}\right] + \sum_{i \in S_m^{end}}\left[(1-\zeta_i)\sum_{j=1}^{J}\text{cost}_{ij}y_{ij}\right] \quad m = 1, 2, \ldots, M \tag{7}$$

$$\sum_{i=1}^{n}\sum_{j=1}^{J} dem_{ijr}\, y_{ij} \le a_r \quad r = 1, 2, \ldots, R \tag{8}$$

$$\sum_{t=E_m}^{L_m} z_{mt} = 1 \quad m = 1, 2, \ldots, M \tag{9}$$

$$\sum_{t=E_{s_i}}^{L_{s_i}}\left(z_{s_i t}.t\right) + \sum_{j=1}^{J}\left(dur_{ij}y_{ij}\right) \le \sum_{t=E_{e_i}}^{L_{e_i}}\left(z_{e_i t}.t\right) \quad i = 1, 2, \ldots, n \tag{10}$$

$$\sum_{m=1}^{M}\left(e_m\sum_{t=0}^{T} z_{mt}\right) \le ICA + \sum_{k=1}^{K}\left[p_k\sum_{m=1}^{M}\left(x_{km}\sum_{t=0}^{T} z_{mt}\right)\right] \quad T = 1, 2, \ldots, D \tag{11}$$

$$\sum_{k=1}^{K} p_k = U \quad k = 1, 2, \ldots, K \tag{12}$$

$$\sum_{j=1}^{J} y_{ij} = 1 \quad i = 1, 2, \ldots, \mathrm{n} \tag{13}$$

$$\sum_{t=E_M}^{L_M} (z_{Mt}.t) \le D \tag{14}$$

$$x_{km},\ z_{mt},\ y_{ij} \in \{0, 1\} \tag{15}$$

The objective function (2) represents the amount of contractor's NPV which is equal to the current value of payments minus all costs associated with the project. The objective function (3) represents the minimization of the total completion time of the project, which is equal to minimizing the final event of the project. Equation (4) denotes the assignment of payment k (k = 1, 2, …, K− 1) to a particular event. Equation (5) ensures that the last payment K should be assigned to the last event M. Equation (6) represents that only one payment occurs in a particular event. Equation (7) calculates total costs of an event. Equation (8) indicates the amount of available resources for activities under each mode. Equation (9) shows the occurrence time of event m in the possible time window $[E_m, L_m]$. Equation (10) denotes the precedence relationships. Here, E_{s_i} and L_{s_i} are the earliest and lateness occurrence time of the event that the activity i begins at it. Furthermore, E_{e_i} and L_{e_i} denote the earliest and lateness occurrence time of the event that the activity i ends at it. Equation (11) ensures that the sum of the contractor's output financial flows should not exceed its initial capital plus the amount of the input financial flows. Equation (12) ensures that the sum of all payments is equal to the contract price of the project. Equation (13) ensures that each activity should be performed only by one execution mode. Equation (14) also ensures that the occurrence time of the final event should not exceed the project delivery time. Equation (15) defines types of the variables.

4 Solution methods

The proposed model is a mixed integer non-linear programming (MINLP) and due to its high complexity, it is NP-Complete [19]. Therefore, implementing heuristic and meta-heuristic approaches is necessary to solve the problem. On the other hand, in order to validate the proposed mathematical model, small-sized samples are solved by GAMS software-BARON solver using the ε-constraint method to cope with the bi-objectiveness of the model.

To solve the problems with large sizes, NSGA-II and MOSA algorithm are designed to solve the problem as the main methods and are evaluated in comparison with each other and the ε-constraint method. NSGA-II is one of the most common and powerful algorithms available to solve multi-objective optimization problems so that its effectiveness in solving various problems has been proven [11]. MOSA algorithm is a fast local search algorithm that has the ability to escape local optimum solutions [16]. This algorithm has much efficiency in solving problems with a discrete or on-convex solution space.

4.1 ε-Constraint method

The ε-constraint method is one of the well-known approaches to deal with multi-objective problems which can generate Pareto solutions [14]. The formulation of the ε-constraint method is as follows:

$$\begin{aligned}&\text{Minimize } f_1(x)\\&\text{subject to}\\&f_2(x) \le \varepsilon_2,\\&\ldots\\&f_n(x) \le \varepsilon_n,\\&x \in X.\end{aligned} \tag{16}$$

The ε-constraint method steps are as follows:

Step 1: Choose one of the objective functions to be introduced as the main objective function.
Step 2: Solve the problem according to each single objective function, then obtain the optimal values of each objective function and the other obtained values for remaining objective functions. If we have n objective functions, we should solve the single-objective model for n times with all objectives. In each single-objective model, n values are determined for all n objective functions.
Step 3: Find the two best values for each sub-objective functions. Divide the difference between these two values to a given number (the number of breakpoints) and create a table of values for $\varepsilon_2, \ldots, \varepsilon_\text{n}$.
Step 4: Now, solve the single-objective model with the main objective function for each value of $\varepsilon_2, \ldots, \varepsilon_\text{n}$.
Step 5: Report Pareto solutions findings.

In our proposed model, the first objective is considered as the main objective and the second objective is the sub-objective with 10 breakpoints. So the formulation is presented as follows:

$$\begin{aligned}&\text{Maximize } f_1(x)\\&\text{subject to}\\&f_2(x) \le \varepsilon_2,\\&x \in X.\end{aligned} \tag{17}$$

4.2 NSGA-II

GA is an efficient algorithm which has been extensively applied to different optimization problems [27, 42, 47].

Srinivas and Deb [40] proposed the non-dominated sorting genetic algorithm for the first time; it divided the evolutionary group into several levels based on a dominance relation for selection and solution. Deb et al. [12] optimized an operational NSGA scale, such that elite mechanism was used instead of sharing coefficient of density function; this algorithm is known as NSGA-II. The proposed pseudo-code of the applied NSGA-II in this research is shown in Fig. 3.

The main information about the mechanism of the proposed NSGA-II is as follows: two-point crossover operator and one-point mutation operator are used for crossover and mutation, respectively. Furthermore, the stopping condition of this algorithm is met when there is no improvement in 50 consecutive iterations. Moreover, the values of the parameters are determined by trial and error method which is described in Table 2.

```
Procedure NSGA-II
  Input: N', g, f_k(X) ▷ N' members evolved g generations to solve f_k(X)
  Initialize Population P';
  Generate random population - size N';
  Evaluate Objectives Values;
  Assign Rank (level) based on Pareto - sort;
  Generate Child Population;
     Binary Tournament Selection;
     Recombination and Mutation;
  for i = 1 to g do
      for each Parent and Child in Population do
          Assign Rank (level) based on Pareto - sort;
          Generate sets of nondominated solutions;
          Determine Crowding distance;
          Loop (inside) by adding solutions to next generation starting from
          the first front until N' individuals;
      end
      Select points on the lower front with high crowding distance;
      Create next generation;
         Binary Tournament Selection;
         Recombination and Mutation;
  end
```

Fig. 3 Pseudo-code of NSGA-II [2]

Table 2 Optimal levels of the parameters for the proposed NSGA-II

Parameter	Value
Initial population	300
Probability of crossover	0.8
Probability of mutation	0.2

4.3 MOSA algorithm

SA is another well-known fast metaheuristic algorithm has been studied to improve the solutions generated initially in different optimization problems [3, 43]. On the other hand, MOSA attempts to generate non-dominated solutions by using a simple probability function that tries to generate solutions on the Pareto optimal front. The probability function is varied in such a way that the total space of objective is covered uniformly obtaining as many possible non-dominated and well-dispersed solutions [46]. These features have made MOSA a fast efficient algorithm compared to the other existing multi-objective algorithms. Figure 4 illustrates the pseudo-code of MOSA algorithm. Furthermore, the mechanism of the suggested MOSA is adopted from that proposed by Kubotani and Yoshimura [24]. Note that MOSA is designed on the basis of SA considering the non-dominance concept, which is implemented by NSGA-II.

The values of MOSA parameters are determined by trial and error method which is represented in Table 3.

5 Numerical results

In this section, model validation, sample problems generation and solution methods evaluation are presented and described.

```
s=s0
T=T0
Repeat
   Generate a neighbor s'=N(s)
   If C(s') dominates C(s)
            move to s'
   else if C(s) dominates C(s')
            move to s' with transition probability
         Pt(C(s), C(s'), T)
   else if C(s) and C(s') do not dominate each other
            move to s'
   end if
   T=annealing(T)
End repeat (until the termination are satisfied)
```

Fig. 4 MOSA pseudo-code [32]

Table 3 Optimal levels of the parameters for the proposed MOSA algorithm

Parameter	Value
Maximum number of iterations in each temperature	5
Initial temperature	300
Temperature reduction rate	0.85
Boltzmann constant	0.2
Final temperature	1

5.1 Sample problems generation

To validate the proposed model and evaluate the developed solution techniques, 12 sample problems are designed in different scales where the input parameters are generated randomly. The required information about these samples is provided in Table 4. Moreover, Fig. 2 represents AOA network of problem 1, and Figs. 5, 6 and 7 depict AOA networks of problems 2–4, respectively. The other samples are so large to show their related AOA networks.

Table 4 Input information about samples

Sample no.	Events no.	Activities no.	Possible modes no.
1	6	6	2
2	10	10	2
3	12	12	3
4	18	18	3
5	20	26	4
6	25	33	4
7	30	40	5
8	35	46	5
9	40	52	5
10	42	55	5
11	45	58	6
12	50	68	6

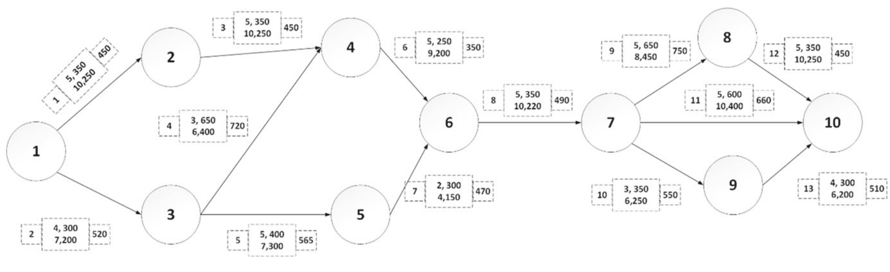


Fig. 5 AOA network of sample 2

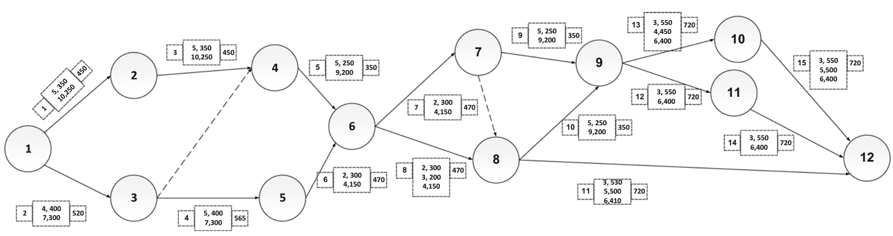


Fig. 6 AOA network of sample 3

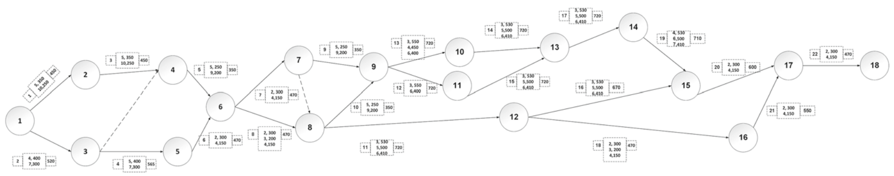


Fig. 7 AOA network of sample 4

Table 5 Optimal values of objective functions for sample problems

Sample no.	Max f_1		Min f_2		Run time (s)
	f_1	f_2	f_1	f_2	
1	– 1245.494	29	– 1853.184	15	81.05
2	– 3709.171	43	– 4346.223	31	1157.68
3	– 4182.31	49	– 4890.108	29	11,823.19
4	– 6316.22	58	– 7426.003	37	12,000
5–12	–	–	–	–	12,000

Table 6 Pareto solutions obtained by NSGA-II, MOSA and ε-constraint method

Pareto point no.	ε-constraint		NSGA-II		MOSA	
	f_1	f_2	f_1	f_2	f_1	f_2
1	– 1352	29	– 1412	33	– 1487	29
2	– 1433	28	– 1490	31	– 1546	28
3	– 1497	27	– 1572	29	– 1614	27
4	– 1544	26	– 1639	28	– 1652	26
5	– 1582	25	– 1728	25	– 1870	23
6	– 1664	23	– 1938	21	– 1982	19
7	– 1722	21	– 1978	20	–	–
8	– 1785	19	– 2010	19	–	–
9	– 1802	18	–	–	–	–
10	– 1842	17	–	–	–	–

It has been concluded that the ε-constraint method cannot solve the samples 5–12 by considering the run time constraint of 12,000 s. Thus, these samples are considered as large-sized problems.

Table 5 represents the obtained results by the ε-constraint method. It's worth mentioning that problems are run on a laptop with specs (Intel Core i7-RAM 8 GB) by GAMS software and BARON MINLP Solver.

In the following, 10 values of epsilons (breakpoints) are considered based on the third step of the ε-constraint method and then 10 Pareto points are obtained after implementing steps 4 and 5. These results are presented in Table 6 for the first sample in comparison with the other solution techniques.

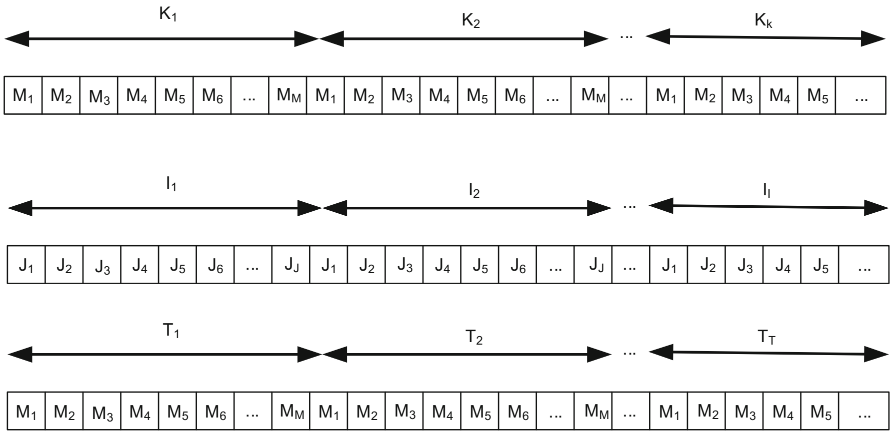


Fig. 8 Chromosome-based solution representation

5.2 Solution representation

In meta-heuristic algorithms, a solution string including binary matrices of $K * M$, $I * J$ and $M * T$ is used to display a feasible solution. Figure 8 shows the defined string related to solution representation.

In the first part, if the payment k is assigned to the event m, the corresponding cell takes the value of 1; otherwise it takes 0. In the second part, if activity i is executed under mode j, the corresponding cell takes the value of 1; otherwise, it takes 0, and finally in the last one, if the event m occurs at period t, the corresponding cell takes the value of 1; otherwise, it takes 0.

5.3 Solution results

In this section, the numerical results obtained by the proposed solution methods are analyzed. First, in small and medium-sized problems, the results of NSGA-II and MOSA algorithms are compared with the results of the ε-constrained method. Since the ε-constrained method is not possible to solve the larger problems within 12,000 run time limitation, these problems are solved by the proposed metaheuristic algorithms and the obtained results are compared using different measures. It should be noted that the proposed algorithms are coded in MATLAB programming language.

Table 6 represents the obtained Pareto solutions by these three solution methods for sample 1. As is clear, NSGA-II could find 8 Pareto solutions and MOSA algorithm has found 6 Pareto solutions for the first sample.

According to Fig. 9, it is clear that the Pareto frontiers obtained by MOSA and NSGA-II are close to one obtained by the ε-constraint method. MOSA algorithm has a better and closer performance than NSGA-II for solving the sample 1. However, for more accurate evaluation of the proposed algorithms, some well-known measures including mean ideal distance (MID) measure, spacing metric (SM), diversification metric (DM) and run time are used. The definition of these measures is explained in

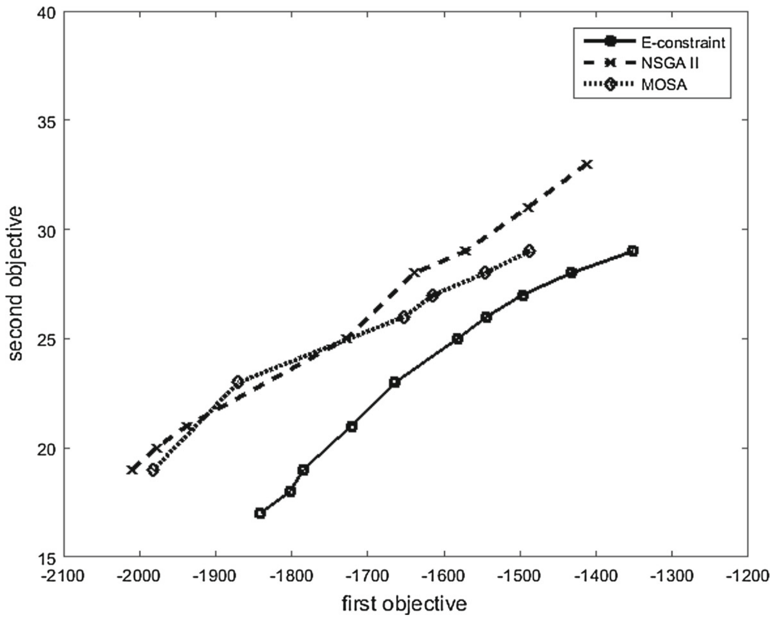


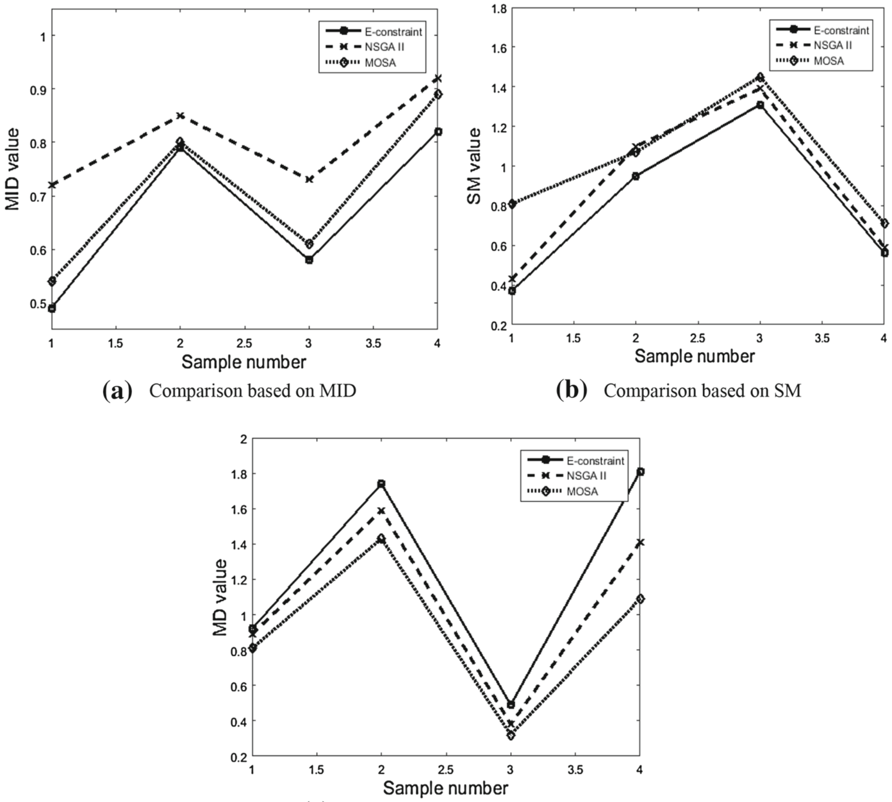
Fig. 9 Pareto frontiers obtained by different solution methods for the first sample

Table 7 Comparison of the proposed solution methods in the small and medium sized samples

Sample no.	Method	MID	SM	DM
1	ε-Constraint	0.49	0.37	0.92
	NSGA-II	0.72	0.43	0.89
	MOSA	0.54	0.41	0.81
2	ε-Constraint	0.79	0.95	1.74
	NSGA-II	0.85	1.1	1.59
	MOSA	0.8	1.07	1.43
3	ε-Constraint	0.58	1.31	0.49
	NSGA-II	0.73	1.39	0.38
	MOSA	0.61	1.45	0.32
4	ε-Constraint	0.82	0.56	1.81
	NSGA-II	0.92	0.59	1.41
	MOSA	0.89	0.71	1.09

Zitzler et al. [49]. The obtained results based on these measures are reported in Table 7 and also depicted in for the proposed methods.

As can be seen in Fig. 10, the proposed meta-heuristic algorithms perform close to the ε-constraint method. MOSA has been better in the measure of MID and NSGA-II could obtain the superior results in terms of DM. However, they are very similar in terms of SM where each one may be better in different small and medium-sized samples. According to the obtained results in these samples, we can conclude that MOSA algorithm is slightly better than NSGA-II, but the important point is that the



(a) Comparison based on MID **(b)** Comparison based on SM

(c) Comparison based on DM

Fig. 10 Comparison of the proposed solution techniques based on different measures in small and medium-sized samples

output of both algorithms is reliable and valid in comparison with the ε-constraint method. Therefore, they can be used as a suitable solution for large-sized problems.

For further investigation, these algorithms are tested on large-sized samples too (Table 8 and Fig. 11).

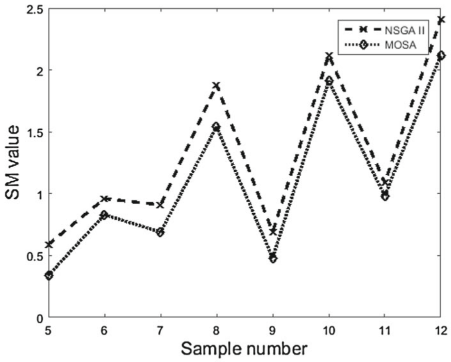
According to Table 8 and Fig. 10, MOSA algorithm has a better performance just in MID measure while NSGA-II outperforms it in terms of SM and DM measures. Therefore, NSGA-II has a better overall performance and can be introduced as the most efficient algorithm to solve large-sized problems.

Finally, the optimal Pareto frontier obtained by these algorithms for a large-sized sample (No. 5) is depicted in Fig. 12.

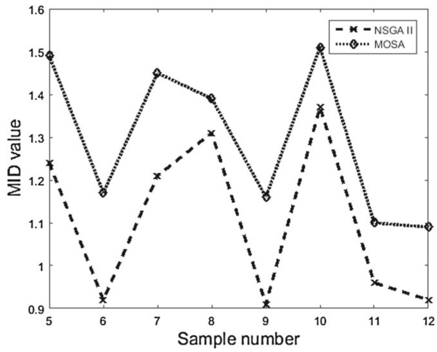
As it is clear in Fig. 12, NSGA-II can find more Pareto solutions than MOSA algorithm. In addition, the distance between two successive Pareto solutions is lower in NSGA-II. But Pareto frontier quality created by MOSA algorithm is much better because this algorithm is able to generate Pareto solutions closer to the ideal point (origin coordinates). Now, as a final comparison of the proposed solution methods,

Table 8 The comparison results of NSGA-II and MOSA algorithm in large-sized samples

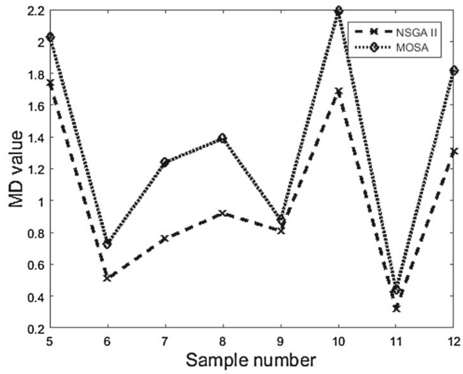
Samples no.	SM		MID		DM	
	MOSA	NSGA-II	MOSA	NSGA-II	MOSA	NSGA-II
5	0.34	0.59	1.49	1.24	2.03	1.74
6	0.83	0.96	1.17	0.92	0.73	0.51
7	0.69	0.91	1.45	1.21	1.24	0.76
8	1.54	1.88	1.39	1.31	1.39	0.92
9	0.48	0.69	1.16	0.91	0.88	0.81
10	1.91	2.12	1.51	1.37	2.19	1.69
11	0.98	1.09	1.1	0.96	0.44	0.32
12	2.12	2.41	1.09	0.92	1.82	1.31
Average	1.11	1.33	1.30	1.11	1.34	1.01



(a) Comparison based on SM



(b) Comparison based on MID



(c) Comparison based on DM

Fig. 11 Comparison of NSGA-II and MOSA algorithm based on different measures in large-sized samples

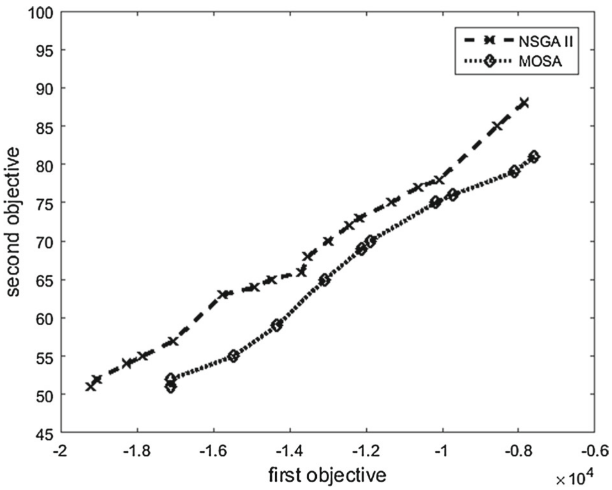
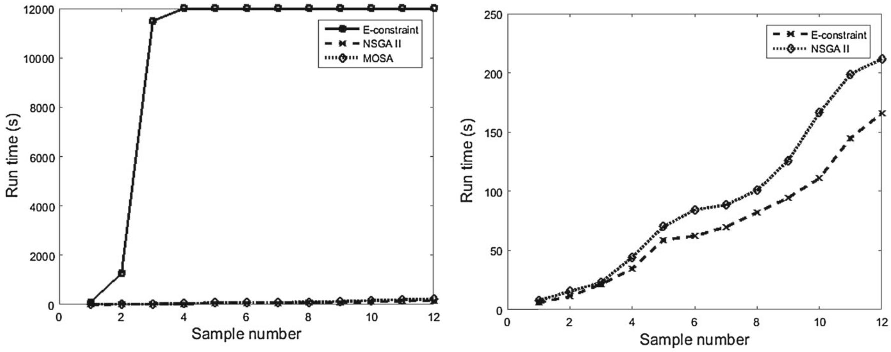


Fig. 12 Pareto frontier of the NSGA-II and MOSA algorithm for the 5th sample



(a) Run time comparison of ε-constraint, MOSA and NSGA-II **(b)** Run time comparison of MOSA and NSGA-II

Fig. 13 Run time comparison of the proposed solution techniques in all samples

they are compared in terms of run time. Figure 13a, b illustrates these comparisons for all the proposed solution methods and two suggested algorithms, respectively.

As it is obvious, the required run time to solve the samples 1–4 by the ε-constraint method is growing exponentially to the extent that it cannot solve the samples 5–12 within the considered time limitation of 12,000 s. However, meta-heuristic algorithms could solve them in a much shorter time. Based on Fig. 13b, NSGA-II requires less run time to find its Pareto frontiers, and it can be the advantage of this algorithm against MOSA.

Consequently, the proposed NSGA-II and MOSA algorithms in this study can be regarded as effective tools for solving large-sized problems in reasonable time. As an important managerial insight, we can see that the time–cost trade-offs would generate solutions with negative NPV, which needs to be analyzed for different situations and goals. Accordingly, the management needs to investigate whether more resources should be provided or not, which can be done by the proposed methodology of this research.

6 Conclusions and suggestions

In this research, a multi-mode resource-constrained project scheduling problem with discounted cash flow (MMRCPSP-DCF) is proposed and formulated based on the real-world conditions considering renewable resources (including manpower, machinery and equipment) as well as non-renewable resources (including consumption and money). Furthermore, payments' planning is studied in the problem which is realized by payments at event occurrence (PEO) model. Thus a bi-objective mixed-integer nonlinear programming (MINLP) model is developed with the aims of NPV maximization and completion time minimization of the project. In order to solve and investigate the validity of the proposed model, different random samples are generated and solved by the ε-constraint method to cope with the bi-objectiveness of the model. On the other hand, two efficient metaheuristic algorithms include non-dominated sorting genetic algorithm II (NSGA-II) and multi-objective simulated annealing (MOSA) algorithm are also developed and implemented to solve the large-sized problems and generate optimal Pareto solutions. Finally, the performance of these solution methodologies is analyzed in terms of mean ideal distance (MID) measure, spacing metric (SM), diversification metric (DM) and run time. The obtained results demonstrate that MOSA algorithm has better efficiency in small-sized problems and NSGA-II outperforms MOSA algorithm in large-sized problems.

The outlook of the research is listed as follows:

(1) Studying uncertainty in the problem, especially in activities demand, cost, or execution time and develop the model using efficient techniques such as stochastic programming, robust optimization, etc.,
(2) Designing and testing other meta-heuristic algorithms such as multi-objective particle swarm optimization (MOPSO) and multi-objective variable neighborhood search (MOVNS),
(3) Considering energy minimization in the project besides the other objectives so that there are a different interval of energy consumptions in each time period,
(4) Investigating different levels of the required skills for each activity under each mode.

Acknowledgements This work was supported in part by International Scientific and Technological Cooperation Project of Dongguan (2016508102011), in part by Science and Technology Planning Project of Guangdong Province (2016A020210142) and in part by Guangdong provincial key platform and major scientific research projects (2017GXJK174).

Funding Funding was provided by International Scientific and Techological Cooperation Project of Dongguan (Grant No. 2016508102011).

References

1. Aboutalebi R, Najafi A, Ghorashi B (2012) Solving multi-mode resource-constrained project scheduling problem using two multi objective evolutionary algorithms. Afr J Bus Manag 6(11):4057–4065
2. Assunção WKG, Colanzi TE, Vergilio SR, Pozo ATR (2013) Generating integration test orders for aspect oriented software with multi-objective algorithms. Revista de Informática Teórica e Aplicada 20(2):301–327

3. Babaee Tirkolaee E, Alinaghian M, Bakhshi Sasi M, Seyyed Esfahani MM (2016) Solving a robust capacitated arc routing problem using a hybrid simulated annealing algorithm: a waste collection application. J Ind Eng Manag Stud 3(1):61–76
4. Bui LT, Barlow M, Abbass HA (2009) A multi-objective risk-based framework for mission capability planning. New Math Nat Comput 5(02):459–485
5. Brucker P, Drexl A, Möhring R, Neumann K, Pesch E (1999) Resource-constrained project scheduling: notation, classification, models, and methods. Eur J Oper Res 112(1):3–41
6. Chen WN, Zhang J (2012) Scheduling multi-mode projects under uncertainty to optimize cash flows: a Monte Carlo ant colony system approach. J Comput Sci Technol 27(5):950–965
7. Chicano F, Luna F, Nebro AJ, Alba E (2011) Using multi-objective metaheuristics to solve the software project scheduling problem. In: Proceedings of the 13th annual conference on genetic and evolutionary computation. ACM, pp 1915–1922
8. Cho SH, Eppinger SD (2005) A simulation-based process model for managing complex design projects. IEEE Trans Eng Manag 52(3):316–328
9. Dayanand N, Padman R (1997) On modelling payments in projects. J Oper Res Soc 48(9):906–918
10. Dayanand N, Padman R (2001) A two stage search heuristic for scheduling payments in projects. Ann Oper Res 102(1–4):197–220
11. Deb K, Agrawal S, Pratap A, Meyarivan T (2000) A fast elitist non-dominated sorting genetic algorithm for multi-objective optimization: NSGA-II. In: PPSN, vol 1917, pp 849–858
12. Deb K, Pratap A, Agarwal S, Meyarivan TAMT (2002) A fast and elitist multiobjective genetic algorithm: NSGA-II. IEEE Trans Evol Comput 6(2):182–197
13. De Reyck B, Leus R (2008) R&D project scheduling when activities may fail. IIE Trans 40(4):367–384
14. Ehrgott M, Gandibleux X (2003) Multi-objective combinatorial optimization—theory, methodology, and applications. In: Gandibleux X (ed) Multiple criteria optimization: state of the art annotated bibliographic surveys. Springer, New York, pp 369–444
15. Geiger MJ (2017) A multi-threaded local search algorithm and computer implementation for the multi-mode, resource-constrained multi-project scheduling problem. Eur J Oper Res 256(3):729–741
16. Glover FW, Kochenberger GA (eds) (2005) Handbook of metaheuristics, vol 57. Springer, New York
17. Hartmann S, Briskorn D (2010) A survey of variants and extensions of the resource-constrained project scheduling problem. Eur J Oper Res 207:1–14
18. He Z, Xu Y (2008) Multi-mode project payment scheduling problems with bonus–penalty structure. Eur J Oper Res 189(3):1191–1207
19. He Z, Wang N, Jia T, Xu Y (2009) Simulated annealing and tabu search for multi-mode project payment scheduling. Eur J Oper Res 198(3):688–696
20. Herroelen W, Van Dommelen P, Demeulemeester E (1997) Project networks with discounted cash flows: a guided tour through recent developments. Eur J Oper Res 100:97–121
21. Hosseini ZS, Pour JH, Roghanian E (2014) A bi-objective pre-emption multi-mode resource-constrained project scheduling problem with due dates in the activities. J Optim Ind Eng 15:15–25
22. Icmeli O, Erenguc SS (1994) A tabu search procedure for the resource-constrained project scheduling problem with discounted cash flows. Comput Oper Res 21(8):841–853
23. Kolisch R, Hartmann S (2006) Experimental investigation of heuristics for resource-constrained project scheduling: an update. Eur J Oper Res 174:23–37
24. Kubotani H, Yoshimura K (2003) Performance evaluation of acceptance probability functions for multi-objective SA. Comput Oper Res 30(3):427–442
25. Küçüksayacıgil F, Ulusoy G (2018) A hybrid genetic algorithm application for a bi-objective, multi-project, multi-mode, resource-constrained project scheduling problem. Sabanci University. http://research.sabanciuniv.edu/34996. Accessed 2 Dec 2018
26. Leyman P, Vanhoucke M (2016) Payment models and net present value optimization for resource-constrained project scheduling. Comput Ind Eng 91:139–153
27. Lu S, Wang S, Zhang Y (2016) A note on the weight of inverse complexity in improved hybrid genetic algorithm. J Med Syst 40(6):1
28. Mika M, Waligora G, Węglarz J (2005) Simulated annealing and tabu search for multi-mode resource-constrained project scheduling with positive discounted cash flows and different payment models. Eur J Oper Res 164(3):639–668
29. Minku LL, Sudholt D, Yao X (2012) Evolutionary algorithms for the project scheduling problem: runtime analysis and improved design. In: Proceedings of the 14th annual conference on genetic and evolutionary computation. ACM, pp 1221–1228

30. Möhring RH (1984) Minimizing costs of resource requirements in project networks subject to a fixed completion time. Oper Res 32(1):89–120
31. Nabipoor Afruzi E, Aghaie A, Najafi A (2018) Robust optimization for the resource constrained multi-project scheduling problem with uncertain activity durations. Scientia Iranica. https://doi.org/10.24200/sci.2018.20801
32. Nam D, Park CH (2000) Multiobjective simulated annealing: a comparative study to evolutionary algorithms. Int J Fuzzy Syst 2(2):87–97
33. Özdamar L, Dündar H (1997) A flexible heuristic for a multi-mode capital constrained project scheduling problem with probabilistic cash inflows. Comput Oper Res 24(12):1187–1200
34. Özdamar L, Ulusoy G, Bayyigit M (1998) A heuristic treatment of tardiness and net present value criteria in resource-constrained project scheduling. Int J Phys Distrib Logist Manag 28(9/10):805–824
35. Oztemel E, Selam AS (2017) Bees algorithm for multi-mode, resource-constrained project scheduling in molding industry. Comput Ind Eng 1112:187–196
36. Russell AH (1970) Cash flows in networks. Manag Sci 16(5):357–373
37. Sebt MH, Afshar MR, Alipour Y (2017) Hybridization of genetic algorithm and fully informed particle swarm for solving the multi-mode resource-constrained project scheduling problem. Eng Optim 49(3):513–530
38. Seifi M, Tavakkoli-Moghaddam R (2008) A new bi-objective model for a multi-mode resource-constrained project scheduling problem with discounted cash flows and four payment models. Int J Eng Trans A Basic 21(4):347–360
39. Sprecher A, Hartmann S, Drexl A (1997) An exact algorithm for project scheduling with multiple modes. OR Spektrum 19:195–203
40. Srinivas N, Deb K (1994) Multi-objective optimization using non-dominated sorting in genetic algorithms. Evol Comput 2(3):221–248
41. Szmerekovsky JG (2005) The impact of contractor behavior on the client's payment-scheduling problem. Manag Sci 51(4):629–640
42. Tirkolaee EB, Hosseinabadi AAR, Soltani M, Sangaiah AK, Wang J (2018) A hybrid genetic algorithm for multi-trip green capacitated arc routing problem in the scope of urban services. Sustainability (2071–1050) 10(5):1–21
43. Tirkolaee EB, Mahdavi I, Esfahani MMS (2018) A robust periodic capacitated arc routing problem for urban waste collection considering drivers and crew's working time. Waste Manag 76:138–146
44. Ulusoy G, Cebelli S (2000) An equitable approach to the payment scheduling problem in project management. Eur J Oper Res 127(2):262–278
45. Ulusoy G, Sivrikaya-Şerifoğlu F, Şahin Ş (2001) Four payment models for the multi-mode resource-constrained project scheduling problem with discounted cash flows. Ann Oper Res 102(1–4):237–261
46. Varadharajan TK, Rajendran C (2005) A multi-objective simulated-annealing algorithm for scheduling in flowshops to minimize the makespan and total flowtime of jobs. Eur J Oper Res 167(3):772–795
47. Wang S, Yang M, Li J, Wu X, Wang H, Liu B, Dong Z, Zhang Y (2017) Texture analysis method based on fractional Fourier entropy and fitness-scaling adaptive genetic algorithm for detecting left-sided and right-sided sensorineural hearing loss. Fundamenta Informaticae 151(1–4):505–521
48. Xiong J, Yang KW, Liu J, Zhao QS, Chen YW (2012) A two-stage preference-based evolutionary multi-objective approach for capability planning problems. Knowl Based Syst 31:128–139
49. Zitzler E, Deb K, Thiele L (2000) Comparison of multi-objective evolutionary algorithms: empirical results. Evol Comput 8(2):173–195

Affiliations

Erfan Babaee Tirkolaee[1,2] · Alireza Goli[3] · Milad Hematian[1] · Arun Kumar Sangaiah[4] · Tao Han[5]

Erfan Babaee Tirkolaee
e.babaee@in.iut.ac.ir

Alireza Goli
a.goli@stu.yazd.ac.ir

Milad Hematian
milad.hemmatian@yahoo.com

Arun Kumar Sangaiah
arunkumarsangaiah@gmail.com

[1] Department of Industrial Engineering, Mazandaran University of Science and Technology, Babol, Iran

[2] Young Researchers and Elite Club, Ayatollah Amoli Branch, Islamic Azad University, Amol, Iran

[3] Department of Industrial Engineering, Yazd University, Yazd, Iran

[4] School of Computing Science and Engineering, Vellore Institute of Technology, Vellore 632014, India

[5] DGUT-CNAM Institute, Dongguan University of Technology, Dongguan, Guangdong Province, People's Republic of China