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Bi-objective Optimization for Resource-constrained Robust Construction Project Scheduling

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ABSTRACT

Construction projects are often executed in complex environments, and various uncertain factors (e.g., bad weather, machine breakdown) prolong activity duration in practice, which may cause project completion delays or profit reduction. Moreover, previous studies often optimized net present value or robustness in project scheduling separately, they neglected the linkage between the value of obtaining NPV and the capacity of tackling uncertainties in a project schedule. To achieve optimal profit and enhance the stability of a project schedule simultaneously, this study proposes a bi-objective optimization for resource-constrained robust construction project scheduling problem (RCRCPSP), which aims at optimizing NPV and robustness, and builds a bi-objective optimization model for the RCRCPSP based on five typical cash flow models. Then an ε-constraints procedure embedded with a genetic algorithm is proposed to solve the model. The ε-constraints procedure performs better than the multi-objective genetic algorithm proposed by the previous study through case study. Furthermore, the findings demonstrate that a trade-off relationship exists between NPV and robustness, and cash flow models have little impact on robustness, while the relaxed deadline can improve a project schedule with high robustness. The fruits of this study can help contractors balance the NPV and the robustness in an indeterministic environment.

1. Introduction

Construction project scheduling is a process of arranging, controlling, and optimizing activities during the project execution, so as to achieve the goals of projects by ensuring the proper use of human and material resources (Hameed and Al-Zwainy, 2022b). However, the limited availability of resources can properly reflect practical scenarios of project management (Franco-Duran and de la Garza, 2020), and some activities executed at the same time may demand more resources than their supply in certain periods. Accordingly, a large number of construction projects are subject to resource limits, so it is necessary for project managers to schedule activities on the background of a resource-constrained environment.

On the one hand, the implementation of construction projects is full of extremely high uncertainties, inaccurate estimation of activity duration, machine breakdowns, and so on. Uncertain factors often change some activities' durations compared to their initial execution times so that projects continue long after their completion times (Liu et al., 2023). In theory, two avenues of techniques have been proposed to tackle uncertainties in project scheduling, namely, stochastic scheduling and robust project scheduling (also known as proactive/reactive project scheduling) (Davari and Demeulemeester, 2019). Compared with stochastic scheduling, robust project scheduling can provide a baseline schedule and then guides schedulers to arrange labor and machine in advance, so the schedule can be executed as the baseline schedule without interruption when the interference of uncertainty factors occurs. Accordingly, it is necessary for practitioners to utilize robust project scheduling to generate a stable project schedule.

On the other hand, uncertainty factors may make a project schedule not be executed according to its baseline schedule, which results in increasing costs and interferes with the status of the project cash flow, even turning a profitable project into a loss-making project, so cost management, scheduling management, and earned value technique may be required for construction projects (Al-Zwainy, 2018; Jaber et al., 2019; Hameed and Al-

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Zwainy, 2022a). Furthermore, construction projects often fail due to cost deviation in their implementation, which may cause by poor cost management, monitoring, or supervision (Al-Zwainy and Mezer, 2018), so it is important for project managers to strengthen profit or cost management in robust project scheduling. In practice, project profit is usually evaluated by the discounted value of cash flows, and the net present value (NPV) is an effective financial indicator that measures profit when project managers consider the time value of money; so numerous previous studies explored the project scheduling optimization problem on NPV maximization in the past (Zhao et al., 2016; Peymankar and Ranjbar, 2021).

Unfortunately, although many studies focused on NPV maximization in project scheduling in the past, as far as our knowledge, the bi-objective optimization that involves NPV and robust project scheduling is completely missed. Moreover, many optimization problems do not involve a single objective, and are often considered as multi-objective problems (Freschi and Repetto, 2006). Furthermore, the trade-off between project revenue and potential uncertainties drives project managers to balance the two factors in project scheduling. Therefore, contractors should optimize profit and robustness in the process of making construction project schedules. To fill the research gap, this study proposes a bi-objective optimization for the resource-constrained robust construction project scheduling problem (RCRCPSP) to optimize NPV and robustness simultaneously, builds a bi-objective optimization model based on five typical cash flow models and common conditions in the resource-constrained project scheduling problem (RCPSP), and develops a corresponding procedure to solve the model. Compared with previous studies, twofold contributions of this study may be presented: 1) a new bi-objective optimization problem is proposed based on five typical cash flow models, in which the robustness measure and financial indicator (NPV) are optimized together; and 2) an effective ε-constraints algorithm is developed to solve the bi-objective optimization model, which can obtain effectively non-dominated project schedules with desirable NPV and robustness.

The rest of the paper is organized as follows: in Section 2, the related literature is reviewed. The research problem definition and mathematical model are given in Section 3. An ε-constraints procedure embedded with a genetic algorithm is explored in Section 4; then the procedure is tested and analyzed by case study in Section 5, and the sensitivity analysis of the case is conducted. Finally, some meaningful conclusions are given in Section 6.

2. Literature Review

Three streams of research problems related to this study are introduced, namely NPV maximization, robust project scheduling, and the corresponding multi-objective project scheduling.

The discounted cash flows in project scheduling problems were first introduced by Russell (1970), thereafter the maximization of NPV in project scheduling has attracted many scholars in the past. Recently, Leyman et al. (2019) employed an iterated local search framework to contrast the impact of different solution presentations on the optimization of NPV for the discrete time/cost trade-off problem according to multiple cash flows and payment models. In addition, some studies considered optimizing NPV in construction projects. Ezeldin and Ali (2017) analyzed and optimized the cash-flow requirements for large engineering portfolios from the contractor's point of view, and proposed a computational model with the objective of maximizing NPV. Asadujjaman et al. (2021) constructed a mathematical model for a resource-constrained project scheduling and material ordering problem with discounted cash flows to achieve optimal NPV. However, these studies assume that a project is executed in a static environment, and its execution will not be disturbed by external uncertainties.

Incorporating the indeterministic factors in NPV maximization, some papers have conducted meaningful exploration recently. Considering stochastic activity durations, Zhao et al. (2016) proposed chance-constrained, expected value, and chance maximization models according to the NPV criterion. Stefan (2018) determined a new continuous-time Markov chain and a backward stochastic dynamic program to schedule activity durations that are modeled utilizing phase-type distributions. Considering the periodical change of cash flows, Peymankar and Ranjbar (2021) established an integer linear programming model and a multi-stage stochastic programming model to maximize NPV in the deterministic and stochastic cash flow cases. However, the above studies cannot provide baseline schedules for project managers.

Different from the aforementioned project scheduling, robust scheduling can tackle uncertainty in project implementation, in which time buffers are often used to represent the robustness of project schedules. Considering the diminishing utility functions of free floats, Lambrechts et al. (2008) designed a new metric of robustness, and it is represented by the cumulative instability weight of each activity. Furthermore, Cui and Zhao (2015) analyzed the application of critical chain buffer management (CCBM) and starting time criticality (STC) for projects with different network characteristics, and compared their performance in solution robustness and quality robustness. Palacio and Larrea (2017) developed a mixed-integer linear programming (MILP) model to maximize the robustness of the free floats of all activities. Compared with robustness proposed in the past, Ma et al. (2019) explored better surrogate robustness measures to generate a robust baseline schedule in an uncertain environment for project managers. Recently, to obtain the optimum project profit, Liang et al. (2019) investigated a robust resource-constrained project scheduling for NPV maximization, and proposed a composite robust scheduling model according to the scenario of stochastic activity duration, then a two-stage algorithm that integrates the SA and TS was designed. From the reactive scheduling perspective, Zheng et al. (2018) first generated robust schedules with the NPV maximization and then employed two reactive scheduling strategies to adjust the infeasible baseline schedules when disruptions occur during project execution. As previously mentioned, few works mainly focus on NPV maximization in robust project scheduling.

Some practical optimization problems not only involve a single objective, but project managers often face decisional problems that implicate multi-objective optimization. The most commonly seen bi-objective optimization is considered project duration minimization and predictive robustness maximization (Davari and Demeulemeester, 2019). As the above-mentioned problem, Hao et al. (2018) developed a robust scheduling method based on hybridization of estimation of distribution algorithm, and utilized the GA to minimize makespan and maximize time-based robustness simultaneously under a chance constraint of satisfying the threshold of capacity-based robustness. Hereafter, Liu et al. (2021) determined the free slack according to start time and renewable resource surplus per unit time, and proposed a variant-genetic algorithm and a variant-simulated-annealing algorithm to optimize robustness and makespan. Since the impact of resource fluctuation and related costs, Abadi et al. (2018) proposed the problems of minimizing the discounted costs of resource fluctuations and minimizing the makespan. In practice, the reactive scheduling is often applied when a proactive schedule becomes infeasible in project execution.

To sum up, the shortcomings of related previous studies are reported in the following three aspects: 1) previous studies tend to separate NPV optimization from robust project scheduling problems, so multi-objective optimization in project scheduling rarely involves NPV and uncertainty measures simultaneously; 2) the existing studies on robust project scheduling with NPV maximization often utilize the sum of free floats or time buffers as the metric of robustness, which cause that some free floats converge on few activities, so the obtained robust project schedule is lack of capacity of resisting disturbance; and 3) some models and summaries are presented based on a certain cash flow model, so some proposed methods or conclusions in previous research may be short of flexibility to deal with practical construction projects.

3. Mathematical Model

3.1 Problem Definition

A project is typically denoted by activity-on-node (AoN), and its network is represented by $G = (V, E)$ where V and E represent the set of nodes (activities, $|V| = J$) and the set of finish-start relationships between activities respectively. In addition, activity 1 and activity J are dummy activities, which means that the two activities only represent the start and the end of a project, so the rest are non-dummy activities. Each activity has only one execution mode, and an activity requires K types of renewable resources during its implementation. R_k and r_{jk} denote the supply of the renewable resource k and the corresponding requirement for activity j in a unit of duration respectively, and the duration of activity j is represented by d_j. The project has a deadline D, which equals the length of critical path multiplied by the coefficient of project deadline β. Besides, the expenditure and revenue will be incurred when an activity is implemented, and the specific cash flow models will be discussed in the next section.

Considering the role of per extra unit of free float with diminishing returns (Lambrechts et al., 2008), this study adopts a free float utility function of activities as the robust measurement (RM) of a project schedule. The RM is determined by Eq. (1), in which CIW_j and ff_j^{rc} separately represent the cumulative instability weight and the free float of activity j. The instability weight refers to the weight factor of an activity's free float utility to the contribution of the RM, and it mainly reflects the impact of activity lateness on its immediate and transitive successors. The larger the instability weight value, the more serious the impact of its delay on the schedule, which is calculated by the number of these successors. Note that an activity should satisfy the renewable resource limit when it is delayed during the scope of the activity's free floats.

$$RM = \sum_{j=1}^{J} CIW_j \sum_{q=1}^{ff_j^{rc}} e^{-q} \tag{1}$$

In practice, practitioners often focus on obtaining the maximum project profit and maintaining an actual schedule that conforms with the initial plan as much as possible, whereas the two goals are closely related to project schedules and cash flows. The optimization problem of this study aims to balance the NPV and robustness by generating multiple non-dominated schedules. Consequently, project managers can achieve the project's NPV maximization and resist some disruptions to some extent by generating a robust project schedule.

3.2 Cash Flow Model

The cash flows of a construction project are connected with the start and finish times of activities, and many scenarios of cash flows were proposed in previous studies. From the perspective of practice, the typical cash flow models contain various types of costs of a project, such as bonding cost, mobilization cost, and direct cost (Alavipour and Arditi, 2018). However, these practical cash flow models lack the elasticity to reflect situations of cash flows encountered by contractors. Consequently, five classic cash flow models proposed by Leyman and Vanhoucke (2017) are applied in this study, as shown in Fig. 1, and they can represent the most of cash flow scenarios in construction projects.

In the classic cash flow models, the total cost of a project is equal to the sum of all activities' costs, and all expenditures of activity j are denoted by c_j. Contractors can receive earned value w_j from clients when they finish activity j ($w_j = c_j \times \gamma$); where γ represents coefficient of earned value. Therefore, contract price U consists of earned values of all activities. As shown in Fig. 1, the cash inflows entirely occur at the finish time of activity j, but the status of cash outflows is different, since contractors may sign different contract terms with suppliers or subcontractors in practice. In Fig. 1, the horizontal axis and the vertical axis represent time t and the corresponding value of cash flows respectively, in which c_j and w_j denote cash outflows and inflows for activity j. For the cash outflow, Model 1 shows that the entire cost of activity j is incurred at its start time, whereas all expenditure is

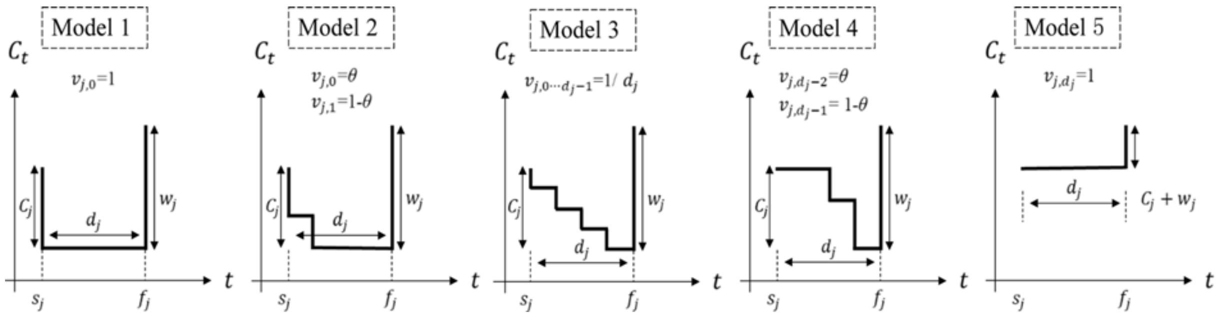


Fig. 1. Scenarios of Cash Flows for an Activity (Leyman and Vanhoucke, 2017)

consumed at its finish time in Model 5; Model 3 represents the cash outflows are paid according to a per time unit basis during the duration of an activity. Model 2 represents that the most cost of activity j (proportion θ) occurs at the beginning of its start time, and the rest cost is consumed at the second unit of the duration next to the start time of activity j, while Model 4 has the completely different form from Model 2.

To determine the NPV in different cash flow models, a group of binary decisional variables is defined as follows, where EF_j and LF_j are determined by the critical path method (CPM) according to the deadline.

$$x_{jt} = \begin{cases} 1 \text{ if activity } j \text{ finished at time } t \; t \in [EF_j, LF_j] \\ 0 \text{ else} \end{cases}$$

Based on the defined decisional variables, Eqs. (2) to (6) present the calculations of the NPV respectively.

Model 1:

$$NPV = \sum_{j=1}^{J} \left\{ w_j \sum_{t=EF_j}^{LF_j} \exp(-\alpha t) x_{jt} - \sum_{t=EF_j}^{LF_j} \exp[-\alpha(t-d_j)] x_{jt} \right\}. \quad (2)$$

Model 2:

$$NPV = \sum_{j=1}^{J} \left\{ w_j \sum_{t=EF_j}^{LF_j} \exp(-\alpha t) x_{jt} - \theta c_j \sum_{t=EF_j}^{LF_j} \exp[-\alpha(t-d_j)] x_{jt} - (1-\theta) c_j \sum_{t=EF_j}^{LF_j} \exp[-\alpha(t-d_j+1)] x_{jt} \right\}. \quad (3)$$

Model 3:

$$NPV = \sum_{j=1}^{J} \left\{ w_j \sum_{t=EF_j}^{LF_j} \exp(-\alpha t) x_{jt} - \sum_{t_p=0}^{d_{j-1}} c_j/d_j \cdot \sum_{t=EF_j}^{LF_j} \exp[-\alpha(t-d_j+t_p)] x_{jt} \right\}. \quad (4)$$

Model 4:

$$NPV = \sum_{j=1}^{J} \left\{ w_j \sum_{t=EF_j}^{LF_j} \exp(-\alpha t) x_{jt} - (1-\theta) c_j \sum_{t=EF_j}^{LF_j} \exp[-\alpha(t-1)] x_{jt} - \theta c_j \sum_{t=EF_j}^{LF_j} \exp[-\alpha(t-2)] x_{jt} \right\}. \quad (5)$$

Model 5:

$$NPV = \sum_{j=1}^{J} \left\{ (w_j - c_j) \sum_{t=EF_j}^{LF_j} \exp(-\alpha t) x_{jt} \right\}. \quad (6)$$

3.3 Optimization Model

According to the problem definition, the mathematical optimization model is constructed according to the defined cash flow models, the robustness measure, and the decisional variables. The objectives are to maximize the NPV of a construction project and the robustness with utility functions of free floats of a project schedule, which are presented in Eqs. (7) and (8) respectively.

$$\text{Maximize } NPV \quad (7)$$

$$\text{Maximize } RM \quad (8)$$

s.t.

$$\sum_{t=EF_j}^{LF_j} x_{jt} = 1, \quad \forall j \in V \quad (9)$$

$$\sum_{t=EF_i}^{LF_i} t x_{it} \le \sum_{t=EF_j}^{LF_j} (t-d_j) x_{jt}, \quad \forall j \in V;\ i \in P(j) \quad (10)$$

$$\sum_{j=1}^{J} r_{jk} \sum_{\tau=1}^{t+d_j-1} x_{j\tau} \le R_k, \quad k = 1,2,\dots,K;\ t = 1,2,\dots,D \quad (11)$$

$$\sum_{t=EF_J}^{LF_J} t x_{Jt} \le D \quad (12)$$

$$x_{jt} \in \{0,1\}, \quad j = 1,2,\dots,J;\ t = EF_j, (EF_j+1), \dots, LF_j \quad (13)$$

Equation (9) ensures that each activity is completed within its time window; Eq. (10) maintains the feasibility of precedence relationship between activity j and its immediate predecessors; $P(j)$ represents the set of immediate predecessors of activity j; Eq. (11) ensures that the requirement of renewable resource k does not exceed the supply at each time unit t; Eq. (12) indicates that the project duration cannot exceed the project deadline; Eq. (13) represents the domain of the decision variables.

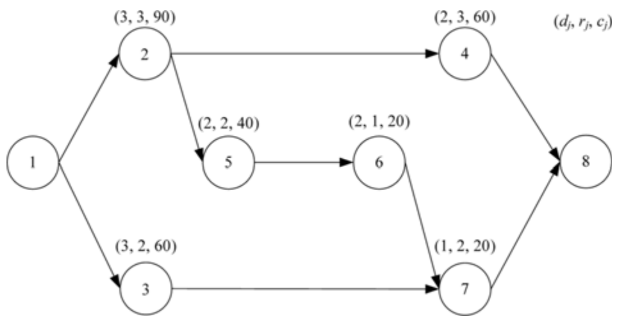


Fig. 2. The Network of an Example

3.4 An Example

A small-scale example with 6 non-dummy activities is to illustrate the differences in five cash flow models and the calculation of robust measurement. The project network of the example is presented in Fig. 2, in which activities 1 and 8 are dummy activities. The number of renewable resources is 5. The numbers above a node represent duration, resource requirement, and the cost of an activity respectively. The coefficient of earned value and the discount rate are 1.4 and 0.01. The deadline is 12.

The cumulative instability weight of an activity refers to the number of its immediate and non-immediate successors. For example, activities 4 and 5 are the immediate successors of activity 2, and its non-immediate successors are activities 6, 7 and 8, so the cumulative instability weight of activity 2 is 5. Accordingly, the cumulative instability weights of activities CIW_j of the example are 0, 5, 2, 1, 3, 2, 1, and 0 in sequence. Three feasible schedules (S_1, S_2, and S_3) are obtained according to cash flow model 1. Schedule S_1 is shown in Fig. 3(a), in which activity 5 and 7 have 1 and 3 free floats respectively, so the robustness is 1.66 ($RM = CIW_5 \times \sum_{q=1}^{1} e^{-q} + CIW_7 \times \sum_{q=1}^{3} e^{-q} = 1.66$), and the NPV is 102.78. In this situation, the delays of activities 5 and 7 within their free floats will not affect the project duration and other activities' execution. Based on the five cash models, the different cash flows of schedule S_1 are displayed in Table 1.

Compared with schedule S_1, although a feasible schedule S_2 has the same project duration in Fig. 3(b), it is dominated by schedule S_1, since schedule S_2 has lower NPV (102.64) and robustness (0.55). Furthermore, non-dominated schedule S_3 is presented in Fig. 3(c), in which NPV and RM are 102.85 and 1.29 respectively, because schedule S_3 has larger but less robustness than schedule S_1. Observing the two objective values of schedules S_1 and S_3, it is clearly found that a trade-off relationship exists between the NPV and robustness.

The non-dominated solutions of the example are listed in Table 2 according to different cash flow models, from which the

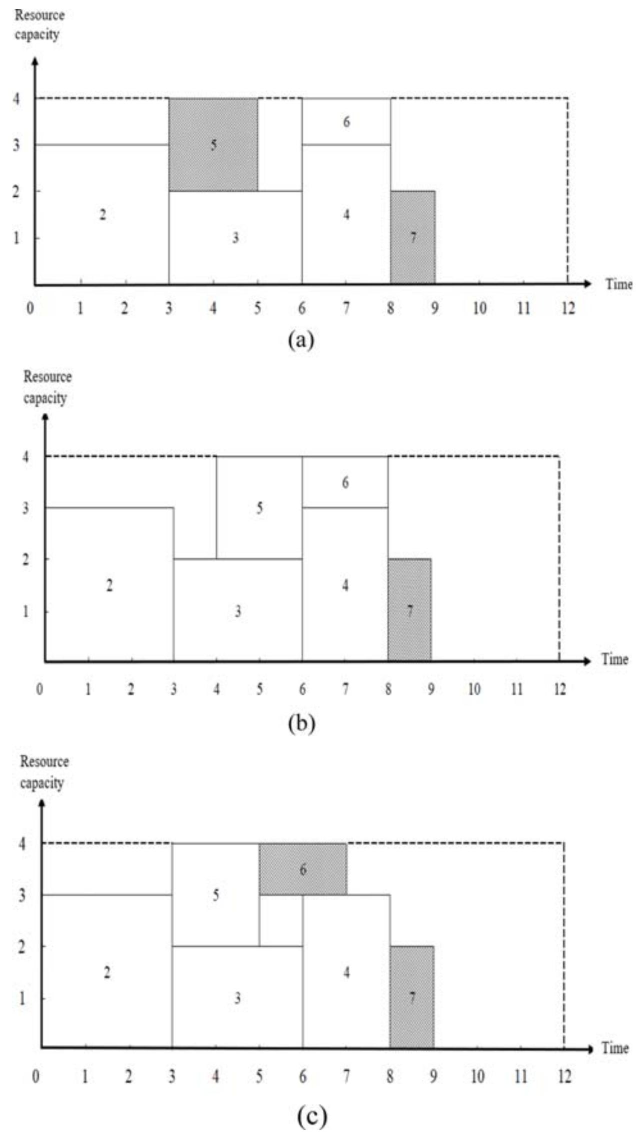


Fig. 3. Project Schedule: (a) S_1, (b) S_2, (c) S_3

Table 1. Cash Flows of Different Models for Schedule S_1

Cash flow status	Cash flow model	NPV	Time									
			0	1	2	3	4	5	6	7	8	9
Cash in			0	0	0	126	0	56	84	0	112	28
Cash out	Model 1	102.78	90	0	0	100	0	0	80	0	20	0
	Model 2	103.90	54	36	0	60	40	0	48	32	12	8
	Model 3	104.82	30	30	30	40	40	20	40	40	20	0
	Model 4	105.82	0	36	54	16	48	36	32	48	20	0
	Model 5	109.61	0	0	0	90	0	40	60	0	80	20

Table 2. Non-Dominated Solutions of an Example

Cash flow	Non-dominated solutions	Net present value	Robustness	Project duration
Model 1	(0,0,3,6,3,5,8,9)	102.85	1.29	9
	(0,0,3,6,3,6,11,12)	102.57	2.76	12
Model 2	(0,0,3,6,3,5,8,9)	103.97	1.29	9
	(0,0,3,6,3,6,11,12)	103.69	2.76	12
Model 3	(0,0,3,6,3,5,8,9)	104.89	1.29	9
	(0,0,3,6,3,6,11,12)	104.61	2.76	12
Model 4	(0,0,3,6,3,5,8,9)	105.89	1.29	9
	(0,0,3,6,3,6,11,12)	105.61	2.76	12
Model 5	(0,0,3,6,3,5,8,9)	109.68	1.29	9
	(0,0,3,6,3,6,11,12)	109.39	2.76	12

negative correlation can be further demonstrated between NPV and robustness. In addition, the schedule with the optimum robustness often accompanies the longest project duration that equates to the project deadline. Contrarily, the alternative with the maximum *NPV* holds a short project duration in different cash flow models.

4. Procedure

The bi-objective optimization model of this study brings challenges for obtaining exact Pareto-optimal solutions. Besides, due to the NP-hardness of the RCPSP with the maximization of NPV (Leyman and Vanhoucke, 2014), the Bi-RCPSP also has a feature of NP-hardness in computational complexity (Tirkolaee et al., 2019).

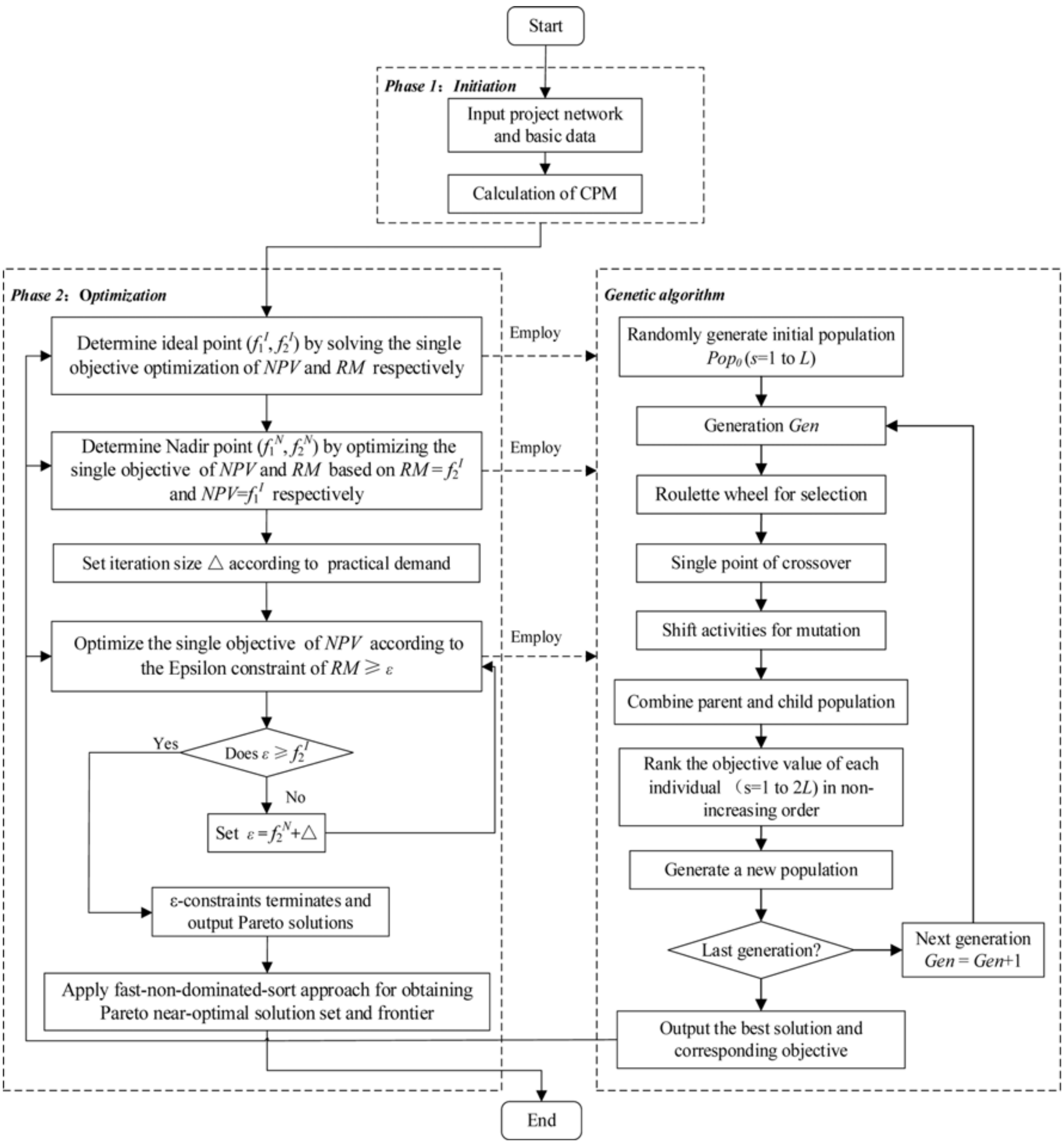


Fig. 4. Framework of Procedure

To obtain high-quality near-optimal non-dominated solutions, an ε-constraints method is developed for the bi-objective RCRCPSP, in which a GA is applied to solve the single objective of NPV maximization for different sizes of projects, and the robustness is transformed into Epsilon constraint.

4.1 Framework of Procedure

The idea of ε-constraints method transforms a multi-objective optimization problem into a series of single-objective optimization problems, then the Pareto-optimal solutions are obtained by solving these problems. Considering the complexity of determining robustness, this optimization objective is converted into Epsilon constraints, so the NPV becomes the exclusive optimization objective. Moreover, meta-heuristics are often developed to solve RCPSP with a single objective, so a GA is designed to search for the best solutions for NPV's maximization. Accordingly, the framework of the procedure is constructed based on the framework of the ε-constraints (Liu et al., 2023), which is shown in Fig. 4. The main steps of the ε-constraints are described as follows:

1. Initialization: the basic parameters of a construction project are input, and the length of critical path is determined by CPM.
2. Determination ideal and Nadir points: the ideal point (f^I_1, f^I_2) consists of the optimum objective values of profit and robustness, where f^I_1 and f^I_2 represent the optimal objective values of NPV and RM in single objective optimization problem based on the constraints of the basic model respectively. Besides, the Nadir point (f^N_1, f^N_2) is defined to determine lower and upper bounds of efficient solutions, and f^N_1 and f^N_2 are obtained by solving the following optimization models, which are shown as Eqs. (14) and (15). Apart from the condition in the equations, the constraints of (9) to (13) also should be satisfied for the two optimization models respectively.

$$f^N_1 = \max\{NPV{:}RM = f^I_2\} \tag{14}$$

$$f^N_2 = \max\{RM{:}NPV = f^I_1\} \tag{15}$$

3. Iteration of solving single objective optimization with Epsilon constraint: the GA solves a serial of the Epsilon constraint optimization problems, which can be represented by Eq. (16), in which ε is increased by a fixed value Δ from f^N_2, namely $\varepsilon = f^N_2 + \Delta$. Moreover, the optimization model also should meet conditions (9) to (13). The Epsilon constraint optimization is terminated when ε is larger than f^I_2.

$$f_1 = \max\{NPV{:}\ RM \geq \varepsilon\}\ . \tag{16}$$

   For above mentioned single objective optimization problems, a GA is designed to solve them, in which a back-forward recursion method adopted from Al-Fawzan and Haouari (2005) is used to determine free floats of activities under resource constraints.
4. Remove the dominated solutions from obtained solutions. A fast-non-dominated-sort approach is utilized to select near Pareto-optimal solutions.

4.2 Genetic Algorithm

4.2.1 Encoding and Decoding

The activity list (AL) is used to represent a feasible solution, which also has been extensively applied in denoting a chromosome in the GA (Xie et al., 2021). The AL contains J activity codes, which determine the order of scheduling activities. Based on the precedence feasibility of the activity list, the AL is decoded by the parallel scheduling generation scheme (PSGS) in the RCPSP (Kolisch, 1996), which arranges as many activities as possible at each scheduling stage, so the start and finish times of activities in project schedules can be acquired.

4.2.2 Genetic Operators

The initial population generation, selection, crossover, and mutation operations are conducted in the process of utilizing the GA, and the algorithm terminates until it reaches the maximum evolutionary generations.

Generation of initial population. Randomly generate $|Pop|$ individuals in the initial population, in which each individual holds the feasibility of priority relationship for all activities.

Selection operation. The strategy of roulette wheel for selection operation is executed in a contemporary population. The fitness value of individual x_i is determined by Eq. (17), in which the fitness value $Fit(x_i)$ is calculated by $F(x_i)$ $(F(x_i) = f(x_i) - f(x)^* + 1)$; where $f(x_i)$ and $f(x)^*$ represent the NPV of individual i and the worst NPV in the current population respectively. Accordingly, the roulette rule calculates the cumulative probability of all individuals, and selects the two individuals as a new population according to the two randomly generating probabilities, and the larger fitness of an individual it is, the more chance to be selected.

$$Fit(x_i) = \frac{F(x_i)}{\sum_{i=1}^{POP} F(x_i)} \tag{17}$$

Crossover operation. Two selected individuals are applied in crossover operator based on crossover probability. A single position is randomly generated between 1 and J, which is used as a crossover point (PO). An offspring inherits a part of father parent's activity list from 1 to PO, and the rest of activity order for the offspring mainly succeeds mother's activity list, and the repetitive activities will not be considered again. Such a method is also applied in the other selected individual, while it first inherits from mother parent's activity list and then from a father.

Mutation operation. For each activity in the activity list, mutation operator is performed according to mutation probability. The strategy of shifting activities is executed for a mutation. An activity is randomly inserted into a position where it locates between the rightmost immediate predecessors of the activity and leftmost immediate successors of the activity. After that, the corresponding activities that rank between the insertion point and the original location of the mutation's activity should be shifted a unit.

Table 3. Project Data

Act	Successor (s)	Duration	Cost ($)	Crews/day	Act	Successor(s)	Duration	Cost ($)	Crews/day
1	2, 3, 4, 5	0	0	0	11	14	25	100	3
2	6, 7	24	1,200	4	12	14, 15	33	320	2
3	12	25	1,000	3	13	18	20	300	2
4	8	33	3,200	2	14	16	30	1,000	3
5	15	20	30,000	3	15	17, 18	18	2,200	5
6	9, 14	30	10,000	2	16	18	16	3,500	6
7	10, 11, 12	24	18,000	3	17	19	30	1,000	3
8	17	24	1,800	2	18	19	24	1,800	3
9	13	18	22,000	4	19	20	18	2,200	2
10	13	24	120	2	20	-	0	0	0

5. Case Study

5.1 Project Data

A case is adopted from Elazouni and Abido (2014) to test the performance of the developed algorithm. Two dummy activities are added in the first and end of the project network, and the project data is shown in Table 3. The parameters setting of the developed algorithm is presented in Table 4. The program of the ε-constraints is coded in Visual Studio C++ (2019), and the calculation of the case is operated on a personal computer with 1.80 GHz CPU and 8G RAM.

Table 4. Parameters Settings

Parameters	Values
Discount rate α	0.01
Coefficient of project deadline β	1.5
Coefficient of earned value γ	1.4
Iteration size	0.1
Population size	100
Maximize generation	200
Crossover probability	0.8
Mutation probability	0.05

5.2 Solving Results

The results of near Pareto-optimal solutions are displayed in Table 5, in which Models 1 and 2 have 9 non-dominated solutions, and the numbers of non-dominated solutions in Models 3, 4, and 5 are 10 respectively. Besides, since the non-dominated solutions in Models 1 and 2 are equal, the procedure found the same value of robustness. Similarly, the values of robustness in the non-dominated solution sets of Models 4 and 5 are identical. Moreover, the maximal and minimal robustness in all cash flow models (14.78 and 7.57) are the same, which means that the different cash flow models have little impact on the size of robustness.

However, it can be clearly found that the *NPV* of Model 5 is the largest but that in Model 1 is the smallest when contrasting the objective of the *NPV* in the five models. The reason is that the cash outflows are all incurred at the completion time of each activity in Model 5, which postpones the time of an activity's expenditure, so the later expenses, the better the *NPV*. Furthermore, although the same non-dominated solutions are obtained (e.g., Models 1 and 2, Models 4 and 5), the values of *NPV* in the five models are completely different. Accordingly, contractors should focus on negotiating with clients or suppliers to sign a contract with good payment terms, which can enhance their project

Table 5. Near Pareto-Optimal Solutions Based on Cash Flow Models

	Model 1		Model 2		Model 3		Model 4		Model 5	
	NPV	RM	NPV	RM	NPV	RM	NPV	RM	NPV	RM
1	8,909.64	7.57	9,199.36	7.57	16,121.10	7.57	22,520.00	7.57	23,343.50	7.57
2	8,686.94	8.13	8,967.48	8.13	15,696.90	7.81	21,982.10	7.81	22,785.90	7.81
3	8,673.48	8.71	8,953.76	8.71	15,651.90	8.13	21,822.40	8.13	22,620.40	8.13
4	8,673.42	10.93	8,953.72	10.93	15,634.10	8.71	21,815.30	9.31	22,613.10	9.31
5	8,595.10	11.44	8,873.15	11.44	15,585.10	10.27	21,802.70	10.93	22,600.00	10.93
6	8,435.68	12.60	8,710.60	12.60	15,501.00	11.44	21,625.80	11.44	22,416.60	11.44
7	8,177.68	13.38	8,446.30	13.38	15,291.80	12.60	21,364.20	12.60	22,145.40	12.60
8	7,313.34	13.92	7,560.90	13.92	14,901.60	13.38	20,857.10	13.38	21,619.80	13.38
9	5,764.16	14.78	5,970.45	14.78	13,607.40	13.92	19,160.00	13.92	19,860.60	13.92
10	-	-	-	-	11,143.30	14.78	15,874.60	14.78	16,455.00	14.78

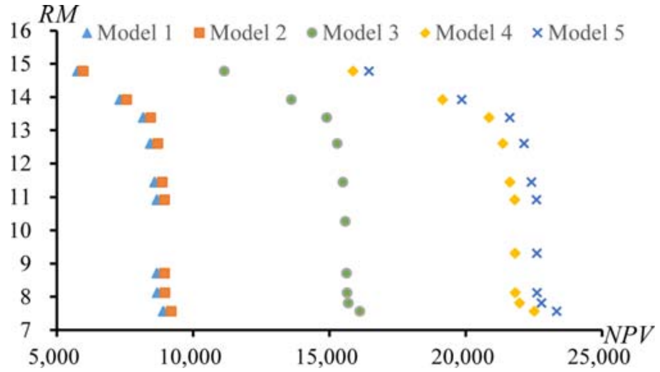


Fig. 5. Non-Dominated Pareto-Optimal Solutions

profits.

Next, the Pareto-frontier's curve of the case is drawn according to the obtained objective function values in the five cash models, which is shown in Fig. 5, it can be observed that the trade-off relationship exists between NPV and robustness in different cash flow models based on the distribution of the non-dominated solutions; in other words, with the increasing NPV, the stability of a project schedule decreases.

In fact, the robustness of a project is determined by free floats when the cumulative instability weight of activities is given, so the robustness is high if a project schedule has a long completion time, in which activities have flexible freedom to be arranged. Accordingly, a schedule with high robustness can be obtained if it finishes at the project deadline, but the delayed schedule often reduces the NPV (Khalili et al., 2013). Contrarily, a schedule with a short project duration diminishes the total of free floats, but the activities are executed earlier than those in a delayed schedule on the whole, so the NPV of a project is large in a short completion time.

5.3 Performance of the Developed Procedure

To verify the effectiveness of the ε-constraints procedure, this study contrasts with a multiple objective genetic algorithm (MOGA) developed by Fonseca and Fleming (1993), since a GA is applied in both the MOGA and the ε-constraints, and they utilize the same operators for a fair comparison. The two algorithms use the same parameter settings, which are shown in Table 4, and they have been executed five times to search for desirable solutions. Consequently, three metrics are applied in evaluating and contrasting the performance of the two approaches, namely spacing, diversity, and hypervolume.

Spacing (*SP*): it reflects the uniformity of the Pareto-optimal solutions, and *SP* is calculated by the standard deviation of distance in all non-dominated solutions, which is determined by Eq. (18) (Schott, 1995). The smaller value of spacing, the better uniformity of Pareto-optimal solutions is.

$$SP = \sqrt{\frac{1}{|P|-1}\sum_{i=1}^{|P|}(\overline{md}-md_i)^2} \tag{18}$$

md_i = the Manhattan distance of non-dominated solution i; $\overline{md}$ = the average value of Manhattan distance md_i; $|P|$ = the number of non-dominated solutions.

Diversity metric (*DM*): it is used to measure the extensiveness and diversity of the Pareto-optimal solutions, which is calculated by Eq. (19) (Deb et al., 2002).

$$DM = \frac{pd_l + pd_f + \sum_{i=1}^{|P|-1}|pd_i - \overline{pd}|}{pd_l + pd_f + (|P|-1)\cdot\overline{pd}} \tag{19}$$

pd_l, pd_f = Euclidean distance between the extreme solutions and the obtained boundary solutions of the non-dominated solution set, where the extreme solutions are generated from the better solutions in the two algorithms.

Hypervolume (*HV*): it assesses the area or volume of the target space surrounded by the non-dominated solutions and the reference point, and its formula is shown in Eq. (20) (Zitzler and Thiele, 1999). The larger value of *HV* indicates the better convergence and diversity of Pareto-optimal solutions.

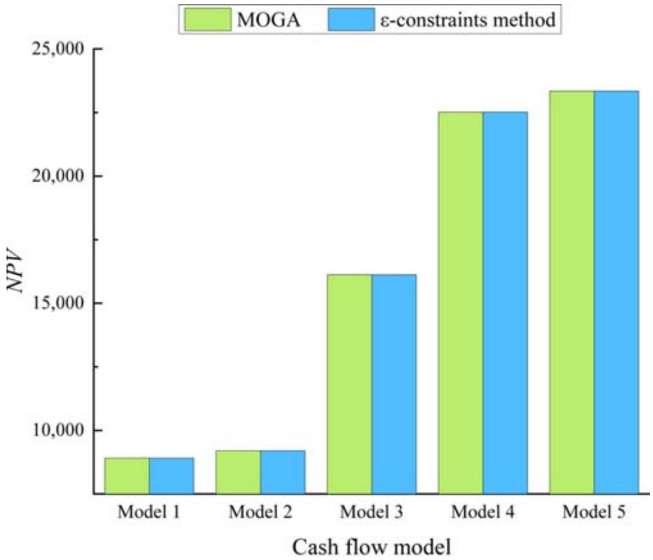
$$HV = \delta(\cup_{i=1}^{|P|} v_i) \tag{20}$$

δ = Lebesgue measure, which is used to calculate the volume, v_i = hypervolume formed by the reference point and the ith Pareto-optimal solution.

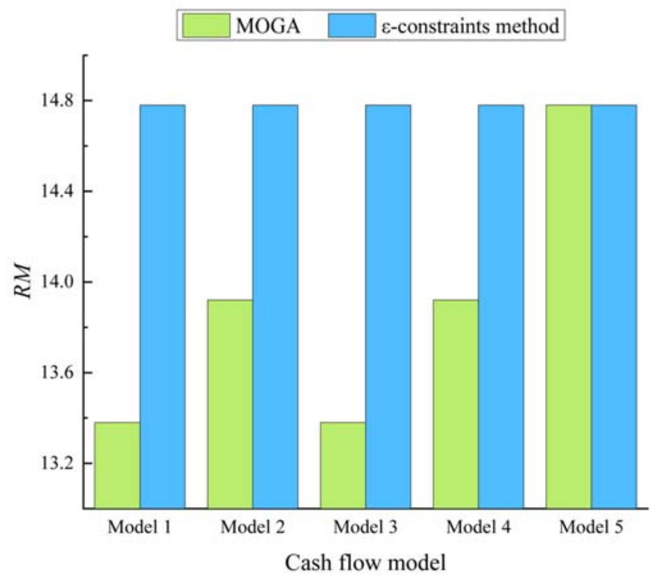
Since the two optimization objectives have the dimensional difference, it is noticed that their values are normalized to an interval [0, 1] respectively. The average values of the three metrics obtained by the two algorithms are displayed in Table 6, in which the metrics of *SP* and *DM* obtained by the ε-constraints method are smaller than those in the MOGA, so the non-dominated solution set found by the ε-constraints has better performance in uniformity and diversity. Besides, the values of *HV* obtained by the ε-constraints method are mostly larger than those in the MOGA, indicating that the ε-constraints method also has more effectiveness than the MOGA in terms of convergence and

Table 6. Performance of the Two Algorithms

Method Metric	ε-constraints				MOGA			
	SP	*DM*	*HV*	CUP time	*SP*	*DM*	*HV*	CUP time
Model 1	0.17	0.47	0.74	969.66	0.21	0.62	0.72	41.22
Model 2	0.17	0.53	0.74	927.33	0.28	0.69	0.73	40.92
Model 3	0.17	0.53	0.72	1,216.83	0.18	0.74	0.70	41.19
Model 4	0.16	0.47	0.74	896.22	0.29	0.80	0.73	42.50
Model 5	0.17	0.46	0.72	946.35	0.24	0.68	0.70	43.46



(a)



(b)

Fig. 6. Comparison of the Extreme Points of NPV and RM Based on the Five Models: (a) The Maximum Value of NPV of the Two Algorithms under the Five Models, (b) The Maximum Value of RM of the Two Algorithms under the Five Models

diversity. However, it can be observed that the computational time of the ε-constraints method is longer than that of the MOGA significantly, because the ε-constraints method executes numerous iterations when the value of ε is updated, in which the application of the GA solves the single objective of NPV repeatedly.

To reflect the effectiveness of searching for the maximum objective (NPV or robustness), the extreme points of the non-dominated solutions between the ε-constraints method and the MOGA are compared, and the results are presented in Fig. 6. In Fig. 6(a), it is clearly found that the maximum values of *NPV* obtained by the two algorithms based on the five models are

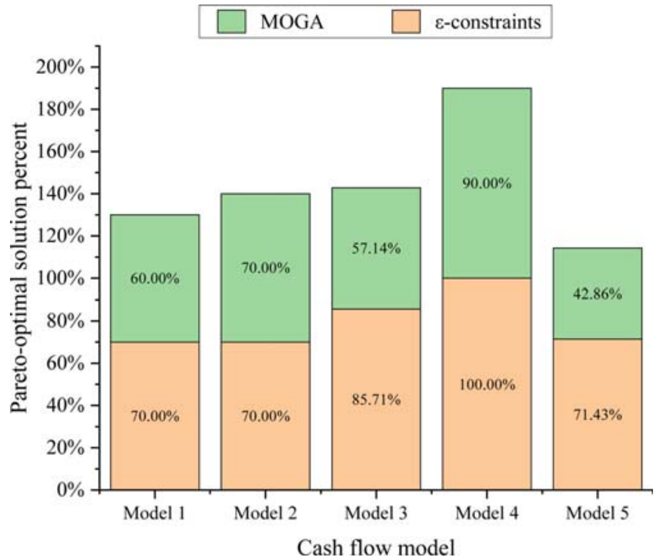


Fig. 7. The Proportion of Non-Dominated Pareto-Optimal Solutions Based on the Five Models

identical. However, for the measure of *RM*, Fig. 6(b) shows that the ε-constraints method captures the larger *RM* than that in the MOGA from Models 1 to 4 respectively, and the two algorithms obtain the identical value of *RM* in Model 5. Accordingly, the ε-constraints method performs well in searching for a single objective. In addition, it is clear that the number of non-dominated solutions (Models 1, 3, 4, and 5) obtained by the ε-constraints method is more than those obtained by the MOGA, which are presented in Fig. 7, which further demonstrates that the ε-constraints procedure can obtain the non-dominated solutions with good convergence and diversity.

5.4 Sensitivity Analysis

To explore the influence of key parameters on the NPV and robustness of construction projects, discount rate α, coefficient of project deadline β, and coefficient of earned value γ are separately considered at different levels based on keeping other parameters unchanged, where cash flow models 1, 3, and 5 are selected due to their obvious difference. Each scenario of parameter permutation is solved by the ε-constraints method, and the average values of objectives are displayed. In Figs. 8, 9, and 10, solid and dotted lines represent the tendency of *NPV* and *RM* respectively.

First, the impact of discount rate α on the two objectives is conducted based on three combinations of β and γ. In Figs. 8(a), 8(b), and 8(c), it is observed that the *NPV* decreases significantly when α increases. Particularly, the variation of the *NPV* in Model 1 is the most significant, decreasing by 59.50%, 49.26%, and 40.85% respectively, while the *NPV* of Model 5 has a smaller change than the results obtained in the other two cash flow models, with decreases of 13.82%, 19.37%, and 16.86%, respectively. However, the robustness does not change obviously, and the reason is that the most of obtained extreme points in Pareto-optimal solutions are the same based on the different levels of

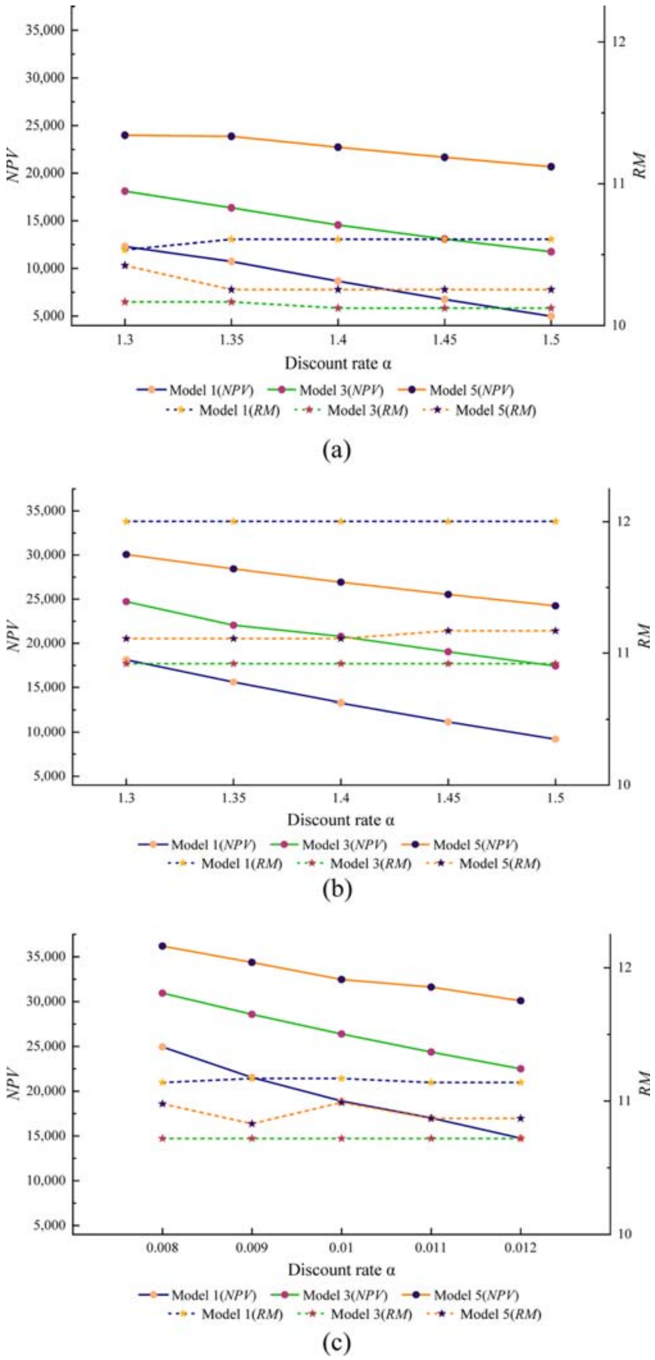


Fig. 8. The Impact of Discount Rate: (a) $\beta = 1.3$ and $\gamma = 1.4$, (b) $\beta = 1.4$ and $\gamma = 1.5$, (c) $\beta = 1.5$ and $\gamma = 1.6$

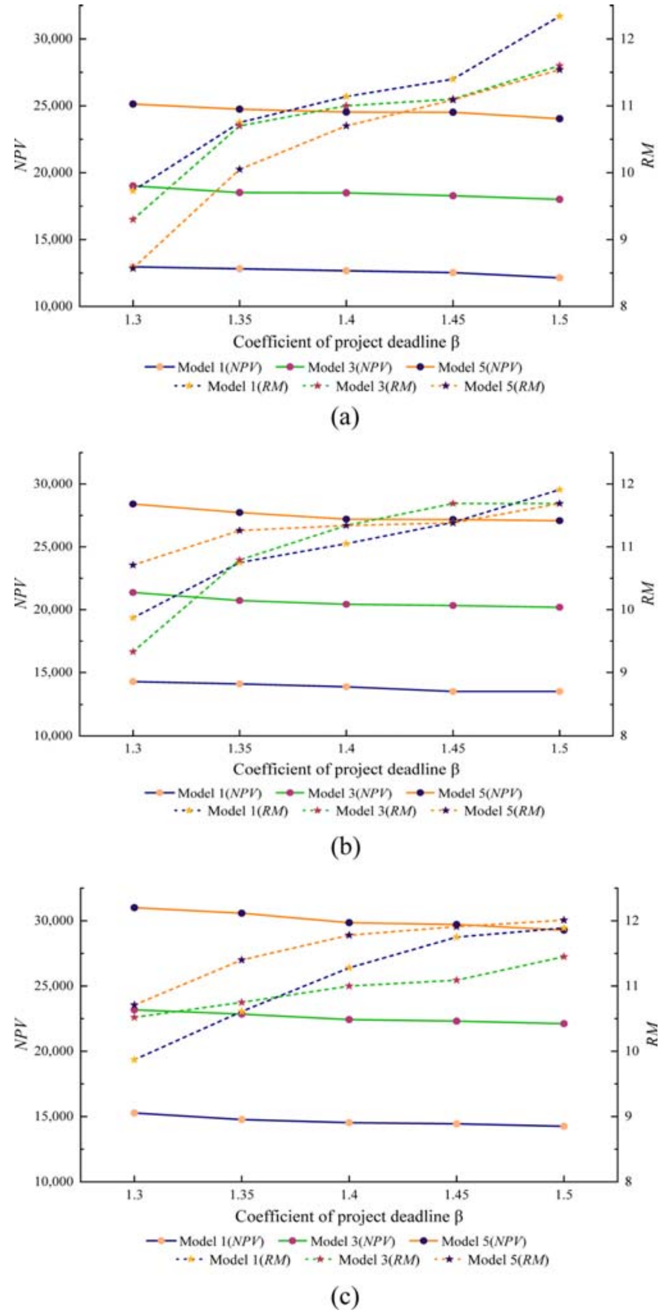


Fig. 9. The Impact of Project Deadline: (a) $\alpha = 0.008$ and $\gamma = 1.4$, (b) $\alpha = 0.010$ and $\gamma = 1.5$, (c) $\alpha = 0.012$ and $\gamma = 1.6$

discount rate. Besides, compared with the results in Fig. 8(a), the results reported in Figs. 8(b) and 8(c) demonstrate that the *NPV* of a project increases when β and γ increase simultaneously.

Second, in Figs. 9(a), 9(b), and 9(c), the robustness of a project schedule increases when the project deadline β is relaxed, while the *NPV* does not change significantly. This is because a project schedule can be embedded more free floats of the activities if a project deadline has lower unstrained, so the robustness of a project schedule performs well. However, the *NPV* of a project is mainly determined by the start and finish times of activities, since it is hardly affected by the size of the free floats of activities. In addition, it can be obviously observed that the values of α and γ have little impact on the robustness based on the same project deadline by contrasting the results in Figs. 9(a), 9(b), and 9(c), but the scenario of combinations of the two factors increases the NPV significantly.

Last, the *NPV* of a project will increase if coefficient of earned value γ enhances, which can be found in Figs. 10(a), 10(b), and 10(c). The maximum *NPV* is obtained when $\alpha = 0.008$ and $\gamma = 1.6$ in Model 5 compared to other scenarios, because the high earned value of an activity will inevitably generate more positive

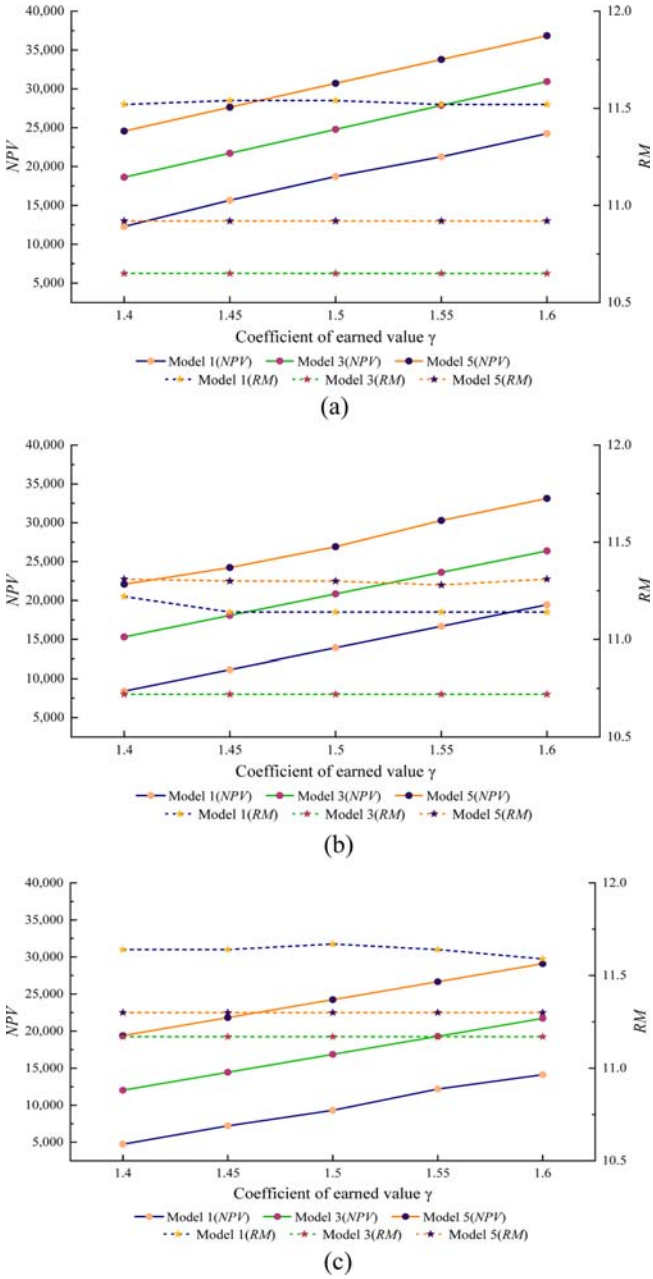


Fig. 10. The Impact of Earn Value: (a) $\alpha = 0.008$ and $\beta = 1.4$, (b) $\alpha = 0.010$ and $\beta = 1.5$, (c) $\alpha = 0.012$ and $\beta = 1.6$

cash flow based on the same project schedule, and the positive cash flow of a project will be improved, so the *NPV* becomes large. However, it can be observed that the robustness changes not obviously, which further verifies that the robustness is insensitive to the variations of earned value. Combined with the impact of discount rate, it indicates that *NPV* is more sensitive to earn value in Fig. 10.

Based on the findings from the sensitive analysis, some managerial insights are refined as follows: 1) contractors should make a reasonable decision in non-dominated schedules between NPV and robustness exists in resource-constrained construction projects based on their risk preference; 2) the favorable financial conditions (e.g., discount rate, earned value) can help contractors gain high profit, but such situation may not improve the capacity of project schedule to tackle uncertainties; and 3) the relax project deadline allowed from clients assists contractors to create a plan with high robustness, but it almost has no impacts on enhancing the *NPV* of a construction project, so contractors can improve cash outflows by negotiating with their subcontractors or suppliers for the arrangement of payments.

6. Conclusions

This study proposes a practical problem of optimizing finance and stability of construction projects simultaneously. Specifically, the main aim is to tackle both the net present value (NPV) and robustness in a same platform according to five common-seen cash flow models. Accordingly, a bi-objective optimization model for a resource-constrained robust construction project scheduling problem is constructed. The goal of the optimization model is to assist practitioners to acquire expected margin through enhancing the robustness when they face an uncertain project environment. Considering the complexity of computation for the optimization model, an ε-constraints method embedding with the GA is proposed, which can obtain near Pareto-optimal solutions. The results of case study demonstrate that the developed algorithm has better performance than the MOGA proposed from a previous study in terms of spacing, diversity, and hypervolume. To enlighten project managers, the sensitivity analysis of key parameters (coefficient of project deadline, coefficient of earned value, and discount rate) is conducted to refine some significant managerial inspiration.

The research findings mainly include as follows: 1) a trade-off relationship exists between NPV and robustness; 2) the cash flow model has little impact on the robustness, but the NPV is sensitive to the occurring times of cash flow; 3) the discount rate and earn value have significant effects on *NPV* respectively, but robustness is positively correlated with the deadline, where *NPV* is more sensitive to the coefficient of earned value. This study can contribute contractors to making a favorable decision between the profit and stability of construction projects when they are executed in an indeterminate environment.

In the future, the fruits of this study should be tested in practical construction projects, or further explored in the background of multiple projects. Besides, some reactive scheduling techniques are expected to be proposed to improve the margin if the schedules of construction projects are interrupted during their implementation.

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References

Abadi NNS, Bagheri M, Assadi M (2018) Multiobjective model for solving resource-leveling problem with discounted cash flows. *International Transactions in Operational Research* 25(6):2009-2030, DOI: 10.1111/itor.12253

Al-Fawzan MA, Haouari M (2005) A bi-objective model for robust resource-constrained project scheduling. *International Journal of Production Economics* 96(2):175-187, DOI: 10.1016/j.ijpe.2004.04.002

Al-Zwainy FMS (2018) A state-of-the-art survey to estimate construction costs in highway and bridge projects: Analytical diagnostic study. *International Journal of Civil Engineering and Technology* 9(5):795-821

Al-Zwainy FMS, Mezher RA (2018) Diagnose the causes of cost deviation in highway construction projects by using root cause analysis techniques. *Arabian Journal for Science & Engineering* 43(4):2001-2012, DOI: 10.1007/s13369-017-2850-2

Alavipour S, Arditi D (2018) Optimizing financing cost in construction projects with fixed project duration. *Journal of Construction Engineering & Management* 144(4):04018012, DOI: 10.1061/(ASCE)CO.1943-7862.0001451

Asadujjaman M, Rahman HF, Chakrabortty RK, Ryan MJ (2021) Resource constrained project scheduling and material ordering problem with discounted cash flows. *Computers & Industrial Engineering* 158:107427, DOI: 10.1016/j.cie.2021.107427

Cui NF, Zhao Y (2015) Buffer methods comparison in robust project scheduling with project network characteristics. *Computer Integrated Manufacturing Systems* 21(1):280-288, DOI: 10.13196/j.cims.2015.01.030

Davari M, Demeulemeester E (2019) The proactive and reactive resource-constrained project scheduling problem. *Journal of Scheduling* 22(2):211-237, DOI: 10.1007/s10951-017-0553-x

Deb K, Pratap A, Agarwal S, Meyarivan T (2002) A fast and elitist multi-objective genetic algorithm: NSGA-II. *IEEE Transactions on Evolutionary Computation* 6(2):182-197, DOI: 10.1109/4235.996017

Elazouni A, Abido MA (2014) Enhanced trade-off of construction projects: Finance-resource-Profit. *Journal of Construction Engineering and Management* 140(9):04014043, DOI: 10.1061/(ASCE)CO.1943-7862.0000880

Ezeldin AS, Ali GG (2017) Cash flow optimization for construction portfolios. *International Conference on Sustainable Infrastructure 2017*, DOI: 10.1061/9780784481202.003

Fonseca CM, Fleming PJ (1993) Multiobjective genetic algorithms. IEEE Colloquium on Genetic Algorithms for Control Systems Engineering. IET Press, London, UK, 6/1-6/5

Franco-Duran DM, de la Garza JM (2020) Performance of resource-constrained scheduling heuristics. *Journal of Construction Engineering and Management* 146(4):04020026, DOI: 10.1061/(ASCE)CO.1943-7862.0001804

Freschi F, Repetto M (2006) VIS: An artificial immune network for multi-objective optimization. *Engineering Optimization* 38(8):975-996, DOI: 10.1080/03052150600880706

Hameed AA, Al-Zwainy FMS (2022a) Statistical evaluation of the planning and scheduling management process for irrigation and drainage projects. *Journal of Algebraic Statistics* 13(2):259-282, DOI:10.52783/jas.v13i2.163

Hameed AA, Al-Zwainy FMS (2022b) Development of duration estimation model for irrigation and drainage projects using neural Network. *NeuroQuantology* 20(6):3041-3053, DOI: 10.14704/nq.2022.20.6.NQ22303

Hao X, Sun L, Gen M (2018) Solving robust resource constrained scheduling problem by multi-objective optimization method based on hybridization of EDA and GA. *Procedia Manufacturing* 17:1187-1194, DOI: 10.1016/j.promfg.2018.10.001

Jaber FK, Hachem SW, Al-Zwainy FMS (2019) Calculating the indexes of earned value for assessment the performance of waste water treatment plant. *ARPN Journal of Engineering and Applied Sciences* 14(4):792-802

Khalili S, Najafi AA, Niaki STA (2013) Bi-objective resource constrained project scheduling problem with makespan and net present value criteria: Two meta-heuristic algorithms. *The International Journal of Advanced Manufacturing Technology* 69(1-4):617-626, DOI: 10.1007/s00170-013-5057-z

Kolisch R (1996) Serial and parallel resource-constrained project scheduling methods revisited: Theory and computation. *European Journal of Operational Research* 90(2):320-333, DOI: 10.1016/0377-2217(95)00357-6

Lambrechts O, Demeulemeester E, Herroelen W (2008) A tabu search procedure for developing robust predictive project schedules. *International Journal of Production Economics* 111(2):493-508, DOI: 10.1016/j.ijpe.2007.02.003

Leyman P, Driessche NV, Vanhoucke M, Causmaecker PD (2019) The impact of solution representations on heuristic net present value optimization in discrete time/cost trade-off project scheduling with multiple cash flow and payment models. *Computers & Operations Research* 103(3):184-197, DOI: 10.1016/j.cor.2018.11.011

Leyman P, Vanhoucke M (2014) A new scheduling technique for the resource–constrained project scheduling problem with discounted cash flows. *International Journal of Production Research* 53(9):2771-2786, DOI: 10.1080/00207543.2014.98046

Leyman P, Vanhoucke M (2017) Capital-and resource-constrained project scheduling with net present value optimization. *European Journal of Operational Research* 256(3):757-776, DOI: 10.1016/j.ejor.2016.07.019

Liang YY, Cui NF, Wang T, Demeulemeester E (2019) Robust resource-constrained max-NPV project scheduling with stochastic activity duration. *OR Spectrum* 41(1):219-254, DOI: 10.1007/s00291-018-0533-3

Liu HR, Qu SJ, Li RJ, Razaa H (2021) Bi-objective robust project scheduling with resource constraints and flexible activity execution lists. *Computers & Industrial Engineering* 156(1):107288, DOI: 10.1016/j.cie.2021.107288

Liu WL, Zhang JW, Liu CF, Qu CL (2023) A bi-objective optimization for finance-based and resource-constrained robust project scheduling. *Expert Systems with Applications*, 120623, DOI: 10.1016/j.eswa.2023.120623

Ma ZQ, Demeulemeester E, He ZW, Wang NM (2019) A computational experiment to explore better robustness measures for project scheduling under two types of uncertain environments. *Computers & Industrial Engineering* 131(5):382-390, DOI: 10.1016/j.cie.2019.04.014

Palacio JD, Larrea OL (2017) A lexicographic approach to the robust resource-constrained project scheduling problem. *International Transactions in Operational Research* 24(1-2):143-157, DOI: 10.1111/itor.12301

Peymankar M, Ranjbar M (2021) Maximizing the net present value in project scheduling under periodic inflation. *Asia Pacific Journal of Operational Research* 38(4):2050057, DOI: 10.1142/S0217595920500578

Russell AH (1970) Cash flows in Networks. *Management Science* 16(5):357-373, DOI: 10.1287/mnsc.16.5.357

Schott JR (1995) Fault tolerant design using single and multicriteria genetic algorithm optimization. *Cellular Immunology*, DOI: 10.1016/0008-8749(78)90168-5

Stefan C (2018) Maximizing the expected net present value of a project with phase-type distributed activity durations: An efficient globally optimal solution procedure. *European Journal of Operational Research* 267(1):16-22, DOI: 10.1016/j.ejor.2017.11.027

Tirkolaee EB, Goli A, Hematian M, Sangaiah AK, Han T (2019) Multi-objective multi-mode resource constrained project scheduling problem using Pareto-based algorithms. *Computing* 101(6):547-570, DOI: 10.1007/s00607-018-00693-1

Xie F, Li HT, Xu Z (2021) Multi-mode resource-constrained project scheduling with uncertain activity cost. *Expert Systems with Applications* 168(4):114475, DOI: 10.1016/j.eswa.2020.114475

Zhao CK, Ke H, Chen ZY (2016) Uncertain resource-constrained project scheduling problem with net present value criterion. *Journal of Uncertainty Analysis and Applications* 4(1):1-15, DOI: 10.1186/s40467-016-0054-z

Zheng WB, He ZW, Wang NM, Jia T (2018) Proactive and reactive resource-constrained max-NPV project scheduling with random activity duration. *Journal of the Operational Research Society* 69(1):115-126, DOI: 10.1057/s41274-017-0198-3

Zitzler E, Thiele L (1999) Multiobjective evolutionary algorithms: A comparative case study and the strength pareto approach. *IEEE Transactions on Evolutionary Computation* 3(4):257-271, DOI: 10.1109/4235.797969