KSCE Journal of Civil Engineering (2022) 26(6):2539-2554
DOI 10.1007/s12205-022-0679-z

pISSN 1226-7988, eISSN 1976-3808
www.springer.com/12205

Construction Management

A Robust Bi-objective Optimization Model for Resource Levelling Project Scheduling Problem with Discounted Cash Flows

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ARTICLE HISTORY

Received 19 April 2021
Revised 30 July 2021
Accepted 11 January 2022
Published Online 31 March 2022

KEYWORDS

Multi-mode project scheduling
Resource leveling
Net present value (NPV)
Robust optimization
Lexicographic Goal Programming (LGP)
Non-dominated sorting genetic algorithm (NSGA-II)
Multi-objective particle swarm optimization (MOPSO)

ABSTRACT

Due to limited financial resources and high costs of infrastructure projects, project stakeholders seek to gain maximum profits with optimal resource utilization as well as cost and time minimization. Therefore, this study presents a multi-mode resource-constrained project scheduling model considering the uncertain parameters of cost and time together with the goals of maximizing the net present value and minimizing resource usage fluctuation. Also, the assumptions related to the real-world projects regarding multi-mode activities, limitation of renewable resources, and the deadline of project are incorporated into the proposed model. Moreover, a robust scheduling method is presented to better deal with the inherent uncertainties of projects regarding cost and time. The model is solved with the exact method named lexicographic goal programming (LGP). Due to the NP-hardness of the problem, two metaheuristic algorithms named Non-dominated Sorting Genetic Algorithm (NSGA-II) and Multi-Objective Particle Swarm Optimization (MOPSO) are applied to solve various medium and large size problems. The obtained results indicate the high efficiency of the two meta-heuristic algorithms in solving the problem and the better performance of the MOPSO algorithm compared with NSGA-II in terms of five indices. Furthermore, the model is implemented in an offshore equipment installation phase of a wellhead platform project. Finally, the sensitivity analysis of the proposed robust model is performed considering different conservation levels, and the results are evaluated by Monte Carlo simulation with three normal, uniform and triangular distributions. The findings demonstrate that the robustness of the model against the variations of uncertain parameters.

1. Introduction

Construction projects comprise a complex network of activities with specific precedence relationships in which each activity can be performed in several execution modes. Since each execution mode exploits a different combination of resources, the time and cost of each execution mode are different. The selection of activity execution modes depends on the goals and constraints of the project. In today's competitive environment, construction companies attempt to maximize profits. In this regard, maximizing net present value (NPV) as the most important indicator of project financial status has been considered by many researchers. Despite many studies have been conducted on the NPV maximization, little research has considered the impact of renewable resources. However, construction projects utilize a variety of renewable resources such as manpower, machinery, equipment, etc., and resource management policies such as resource leveling affect project duration and cost. Resource leveling minimizes fluctuations in resource usage over project horizon.

Scheduling and resource allocation as well as budgeting and financing throughout the implementation of a construction project are among the essential issues in project planning. One of the important and challenging tasks of project management related to the design and implementation stages is proper and efficient scheduling of activities with regard to the limited resources.

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Project scheduling problems have been studied considering different project goals and objectives, various circumstances and constraints arising from the financial or technical aspects of projects (Sallam et al., 2021). Project scheduling problems include an extensive range of optimization problems such as minimizing project completion time and project costs or maximizing net present value. In addition to different objective functions, several assumptions of the real-world problems can be taken into account (Slowinski, 1981).

The main objective of the project scheduling problem is to find a suitable schedule regarding the existing and predefined constraints in the project. The project objectives can be categorized into time-based goals (such as minimization of the total project duration), cost-based goals (such as minimization of the total project costs), and goals based on financial indicators (such as maximization of the net present value) (Hartmann and Briskorn, 2010). Resource-Constrained Project Scheduling Problem (RCPSP) has been known as NP-Hard problems in the field of operations research and project management (Blazewicz et al., 1983). Today, the construction industry is challenging with the detrimental effects of the economic crisis and the COVID-19 pandemic. Thus, the real-world project financing systems and the factors affecting project costs are among the important issues associated with project cost management.

A review of previous studies has demonstrated that a significant number of projects have been unsuccessful regarding the pre-determined time and cost goals. Researchers believe that these types of failure in project management are due to the lack of sufficient attention to uncertainties in project planning and scheduling (Williams, 2017). A lot of studies have yet been published in the field of project scheduling. Two main reasons can be enumerated for this: 1) These types of optimization problems are very extensive according to different conditions, objective functions, characteristics of activities, resources, and precedence relationships; 2) Scholars have tried to introduce more efficient heuristic and metaheuristic methods for solving these types of NP-hard problems (Brucker et al., 1999).

Project schedule is developed by selecting execution modes of activities considering the precedence relationships among activities. Time and resource constraints are defined according to the conditions, goals and objectives of the project. In project scheduling problems with predefined deadlines, the activities can be performed with different combinations of renewable resources which leads to increased costs and uneven level of resource consumption during the project. On the other hand, in resource-constrained project scheduling problems, the precedence relationships among activities and limited amounts of available resources are taken into consideration. Time-cost trade-off and resource leveling problems are known as the project resource-constrained project scheduling problems with predefined deadlines.

Therefore, a method should be proposed to assist project managers with scheduling and selecting the appropriate execution modes of project activities whereby the project is accomplished within the minimum possible duration, the lowest cost, and consequently the maximum profit gained considering the existing uncertainties.

However, past studies have mostly considered projects with deterministic environment and complete information neglecting several uncertainties that influence the duration and cost of each of construction project activities. Hence, taking uncertain parameters associated with the durations and costs of project activities into consideration is crucial in order to achieve a reliable and accurate project plan. This paper proposes a multi-mode resource-constrained project scheduling model taking both resource leveling problem (RLP) and net present value problem (NPV) into account under uncertainty conditions. The two objective functions of the model include maximization of NPV and minimization of resource usage fluctuation. In this study, a robust bi-objective multi-mode resource-constrained project scheduling model is developed considering changing project conditions and uncertainties. The two objective functions consist of maximizing the net present value and minimizing resource usage fluctuation.

This paper is structured as follows. Section 2 investigates the studies related to net present value and resource leveling. Section 3 explains the proposed mathematical programming model along with the solution methodology. Section 4 expresses the implementation of the proposed model in several examples and the sensitivity analysis. Finally, section 5 presents conclusions and suggestions for future research.

2. Literature Review

2.1 Net Present Value (NPV) Problem

Project cost management is a set of complex and essential processes in project management and project managers need to have required knowledge and skills in this field. Project managers' competencies in accurately predicting cash flows of implementation stages lead to remarkable advances in project cost management. Moreover, the accurate prediction of cash flows for construction projects provides real insights for project managers to identify problems and prevent project failures (Mirnezami et al., 2020).

The cash flow term, which is one of the most important financial indicators of a project, is considered as a complete record of all incoming and outgoing financial flows. This means that it includes all costs and revenues in project implementation (Mohagheghi et al., 2017). Cash flow management involves steps that maintain a balance between project revenues and costs and seeks to balance financial inflows and outflows throughout the project life cycle and monitoring them (Shash and Qarra, 2018).

The objective function for maximizing the net present value (NPV) of project cash flows was first proposed by Russell (1970) for the project scheduling problem regardless of resource constraints. They considered both the project employer and contractor seek to increase their return on investment and financial gain. Indeed, the contractor wants to receive the total budget in the shortest possible time, while discrete and intermittent payments of the employer increase the NPV in favor of the employer.

Erenguc et al. (1993) first introduced the time-cost trade-off problem with cash flows. They examined the problem by increasing direct costs in order to reduce the durations of activities. They tried to determine the start time of activities and find the project schedule to maximize the NPV of the entire project. Deckro et al. (1995) studied the time-cost trade-off problem with continuous durations of activities and specific project completion time. They considered the quadratic cost objective function with budget constraints and examined the changes in the values of this objective function with increasing deviations of activity durations. They also took a system of penalties and rewards into account for earliness and tardiness in project delivery times. Icmeli and Erenguc (1996) proposed a novel scheduling model for discrete time-cost trade-off problems with cash flows. They increased the allocated resources to decrease the normal durations of activities and maximized the NPV of the entire project considering the preemption costs of activities. Finally, they solved the model by combining three hierarchical algorithms and compared the results with the Lagrange upper limit method. Dayanand and Padman (2001a, 2001b) presented several mixed-integer linear programming models taking clinet's viewpoint into consideration for project payments.

Mika et al. (2005) developed a model to increase NPV in favor of the contractor using Tabu Search (TS) and Simulated Annealing (SA) algorithms, considering four payment models (total payment at the end of the project, payments at the end of activities, payments in regular intervals, payments based on business progress). Najafi and Niaki (2006) proposed a model for the resource investment problem with the objective function of the project cash flow considering renewable resources and a bonus/penalty system and applied a genetic algorithm (GA) to solve the model. Liu and Wang (2008) presented a resource-constrained project scheduling model for maximizing project cash flow in which profits are maximized according to the project contractors' viewpoints. Afshar Nadjafi and Shadrokh (2009) introduced a branch-and-bound method to tackle the project scheduling problem without resource constraints considering the time value of money with steady cash flows and the minimum and maximum time intervals between activities.

Kazemi and Tavakkoli-Moghaddam (2010) presented the bi-objective project scheduling model considering positive and negative cash flows for maximizing the NPV of the project and minimizing the total project duration. Xiong et al. (2012) examined the multi-objective project scheduling problem with resource constraints to minimize project completion time and maximize the project robustness and stability. They employed a novel hybrid multi-objective evolutionary algorithm (H-MOEA) based on the NSGA-II algorithm. Zhang and Elmaghraby (2014) evaluated the impact of cost progression on financial risks during project implementation using Monte Carlo simulation and the concept of alphorn of uncertainty. They assumed the duration and cost of each activity as random variables. They also considered the cumulative cost at each point in time during the project's progress as a random variable. Finally, they demonstrated that payment rules could significantly affect the financial situation during the execution of a project.

Ning et al. (2017) proposed the multi-mode cash flow balanced project scheduling problem (MCFBPSP) aiming to minimize the maximum gap between outgoing and incoming cash flows of contractors. They used Simulated Annealing (SA) and Tabu Search (TS) metaheuristic algorithms to solve the problem. Leyman et al. (2019) investigated the discrete time-cost tradeoff problem (DTCTP) with the objective of maximizing NPV and analyzed three payment models, each of which determines the time interval and the amount of cash flow based on the contractors' viewpoints. These three payment models include: 1) The total cost (value) incurs (creates) at the start of activity, 2) cost (value) occurs (creates) in steps during the activity execution, 3) the total cost (value) incurs (creates) at the end of each activity. The results of this study indicated that there is a statistically significant difference between these three types of payments in a project scheduling problem.

Cheng et al. (2020) proposed a model for forecasting project cash flow because of its importance in the successful management of project costs. They expressed that the cash flow of construction projects is strongly influenced by sequence and non-sequence factors. They also suggested a new inference model based on artificial intelligence called symbiotic organisms search-optimized neural network-long short-term memory (SOS-NN-LSTM) considering the complexity of projects.

2.2 Resource Leveling Problem (RLP)

The resource-constrained project scheduling problems (RCPSP) with discounted cash flows deal with project scheduling taking the activity precedence relationships and resource constraints into account. If the resource usage of project activities per unit of time exceeds the resource availability, the activities will be shifted to overcome this problem. In such problems, no attention is paid to the resource consumption pattern throughout the project horizon.

The resource leveling problem (RLP) attempts to find a project schedule with an appropriate resource consumption level throughout the project duration considering activity precedence relationships and resource limitations. Indeed, their goal is to minimize the fluctuations of resource consumption during project without changing the project completion time. In other words, resource leveling is a process that minimizes changes in resource usage over time and therefore reduces volatility in resource consumption over project duration. These fluctuations reduce productivity and increase production costs. One of the first efforts for reducing resource usage fluctuations was made by Burgess and Killebrew (1962). Neumann and Zimmermann (2000) investigated the resource-constrained project scheduling problem considering the usual time constraints (including the minimum and maximum time lags between the start times of two activities). They proposed a model taking both resource leveling and NPV into consideration and solved the problem with a branch-and-bound method.

Anagnostopoulos and Koulinas (2010) used a Simulated Annealing Hyperheuristic method to solve RLP. In addition, Ding and Wang (2011) tackled RLP using Ant Colony Optimization (ACO) algorithm. Tang et al. (2013) applied the resource leveling to scheduling the railway construction projects. They proposed a linear programming model for RLP. Asgari et al. (2014) developed a game theory-based approach to solve RLP in the construction industry. Benjaoran et al. (2015) considered other types of activity precedence relationship for RLP and applied the GA to solve it. Damci et al. (2016) examined different ten types of objective functions for resource leveling proposed by several researchers shown in Table 1.

Successful management of construction projects depends on time and cost. On the other hand, resources directly affect project time and costs (Giran et al., 2017).

Table 2 briefly displays the related studies conducted on NPV and RLP as well as the contributions of the present research.

In project scheduling problems, reducing project execution time is possible by allocating more resources, although reducing project execution time leads to increased additional costs. The time-cost trade-off problem aims to find the best executable project schedule regarding the specific project circumstances (Csordas, 2017). Utilization of more resources decreases the project completion time. Therefore, project managers should pay more attention to the resources since resources have greater impacts on project time and cost (Taheri Amiri et al., 2018).

According to the literature review, no study has considered the financial indicators and cash flows associated with project activities in RLP. In addition, most studies have taken definite distribution functions into account for uncertain parameters. However, determination of exact distribution functions for the

Table 1. Different Objective Functions for Resource Leveling Problem (Damci et al., 2016)

No	Type of objective function (Optimization Criteria)	No	Type of objective function (Optimization Criteria)
1	Minimization of the sum of the absolute deviations in resource usage for a determined time interval (day, week etc.)	6	Minimization of the maximum absolute deviation between resource usage for a determined time interval (day, week etc.) and the average resource usage
2	Minimization of the sum of the only increases in resource usage for a determined time interval (day, week etc.)	7	Minimization of the sum of the square of resource usage for a determined time interval (day, week etc.)
3	Minimization of the sum of the absolute deviations between resource usage for a determined time interval (day, week etc.) and the average resource usage	8	Minimization of the sum of the square of the deviations in resource usage for a determined time interval (day, week etc.)
4	Minimization of the maximum resource usage for a determined time interval (day, week etc.)	9	Minimization of the sum of the square of the deviations between resource usage for a determined time interval (day, week etc.) and the average resource usage
5	Minimization of the maximum deviation in resource usage for a determined time interval (day, week etc.)	10	Minimization of the sum of the idle and nonproductive resource days during the entire project duration

Table 2. A Brief Review of the Relevant Studies

Authors	Year	Objective Functions		Data	Activity	Resource constraints	Time constraint	Solving method
		NPV	RLP					
Asadujjaman et al.	2021	✓	-	C	S	✓	✓	ND
Mehrdad	2020	✓	-	C	M	✓	✓	ND
Mirnezami et al.	2020	✓	-	U	M	-	✓	D
Leyman et al.	2019	✓	-	C	M	-	✓	ND
Chaharsooghi et al.	2019	✓	-	C	S	✓	-	ND
Prayogo & Kusuma	2019	-	✓	C	S	-	-	ND
Eydi & Bakhshi	2019	✓	-	U	S	-	-	ND
Li & Dong	2018	-	✓	C	M	✓	✓	ND
Ning et al.	2017	✓	-	U	M	-	✓	ND
Damci et al.	2016	-	✓	C	M	-	-	D
Nikoofal S.A. et al.	2016	✓	-	C	S	✓	✓	ND
Benjaoran et al.	2015	-	✓	C	S	-	✓	ND
Icmeli & Erenguc	1996	✓	-	C	S	✓	✓	ND
This Paper	-	✓	✓	C	M	✓	✓	D (LGP, Robust) ND (NSGAII, MOPSO)

Data (C: Certain, U: Uncertain)/Activity (S: Single Mode, M: Multi-Mode)/GPR (Generalized Precedence Relations)/Solving Method (D: Deterministic, ND: Nondeterministic)

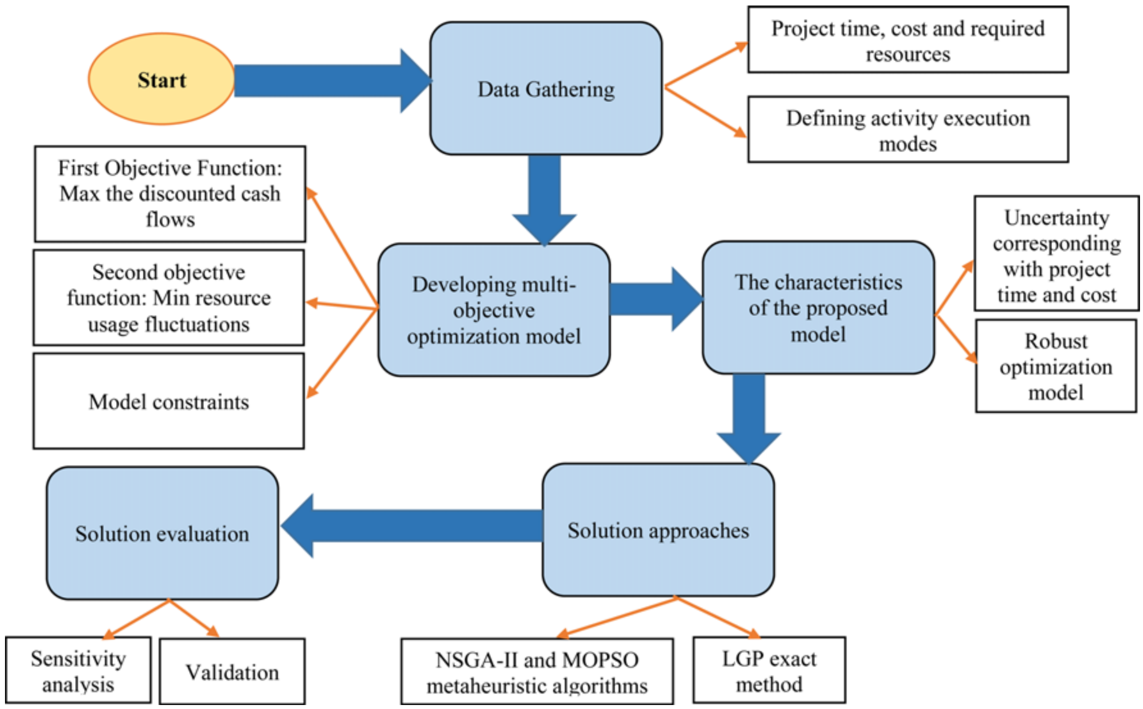


Fig. 1. The Flowchart of the Research Steps

parameters of project scheduling problems is a very challenging burdensome issue. As a result, a robust approach can be a perfect solution to deal with these uncertain conditions in the field of project scheduling problems. In studies conducted on robust project scheduling with strict pessimistic or scenario-based approaches, most of the collected data have been lost and parts of the solution space have been ignored. Hence, the flexible approach proposed by Bertsimas and Sim (2004) with an appropriate coverage level of uncertain data can effectively deal with these problems. Moreover, this approach can be beneficial for executives' decision-making.

Figure 1 shows the steps of this study.

3. Methodology

3.1 Mathematical Programming Model

It is assumed that the project network consists of n activities plotted by an Activity-On-Node (AON) network as a graph G = (V, E), in which nodes (V) represent activities and edges (E) represent precedence relationships among activities. Each activity requires one or more different renewable resources, which may be machine, equipment, or human resources. In this model, several execution modes are defined for each activity, and each activity can be accomplished in only one execution mode. An activity can be executed whenever all its precedence activities have been completed and the resources required for that activity are available. The first and last activities are also considered dummy activities representing the start and finish of the project.

This paper examines the Resource-Constrained Project Scheduling Problem (RCPSP) with two objective functions of maximizing project net present value and minimizing the deviations of resource consumption from the average resource consumption level throughout the project horizon. The assumptions of the proposed model are as follows:

1. Activities do not require setup time.
2. The precedence relationship of the activities is considered as finish-to-start (FS) with zero time lag.
3. Resource capacity is specific and limited.
4. Any activity can use one or more renewable resources at the same time.
5. Having selected an execution mode for an activity, it must be executed in that mode only to be finished.
6. Activities cannot be interrupted.
7. Progress percentage is specified at the end of each activity and the payments are made.
8. Expenses include direct costs associated with executing each activity as well as indirect costs.
9. The durations of activities and project payments have uncertain amounts.

Indices, parameters, and variables of the mathematical programming model are defined as follows:

3.1.1 Sets and Indices

i = Number of Project activities ($i = 1,\ldots, n$)
K = Set of renewable resources
m = Execution modes of activity i ($m = 1,\ldots, M$)
N = Set of Project Activities
P_j = Set of predecessors of activity j
t = Time periods ($t = 1,\ldots, T$)

3.1.2 Parameters

A = The set of arcs where the activity (i, j) has of the precedence relation of finish-to-start. That is, the j-th activity starts after the finish of the i-th activity

C_{imt} = Cost of execution mode m of activity i at time period t

C_{in} = Daily indirect cost of project

d_{im} = Duration of execution mode of activity i

DL = Project deadline

$e^{-\alpha t}$ = Exponential function used to cash flow

ES_i = The earliest time to start the i-th activity

h = Penalty cost of resource fluctuation

LS_i = The latest time to start the i-th activity

NPV = Net Present Value of the project

Pa_{imt} = Cash inflow of execution mode m of activity i at time period t

R_{dev} = Resource usage fluctuation

r_{imk} = Renewable resource k required for execution mode m of activity i

R_k = Available amount of renewable resource k

S_n = Duration of total project

α = Discount rate per time period

3.1.3 Decision Variables

$r_k(t)$ = Usage of renewable resource k at time period t

$$x_{imt} = \begin{cases} 1 & \text{if activity } i \text{ is perforemed in execution mode } m \text{ and started at time } t, \\ 0 & \text{otherwise} \end{cases}$$

$$\forall t \in \{ES_i, \ldots, LS_i\}$$

The objective functions and constraints of the proposed mathematical programming model for the problem are described as follows:

3.1.3.1 Maximization of the Net Present Value

Cash flow is one of the most important financial indicators of project, which is equal to the difference between project revenues and costs. In the proposed mathematical model, payments are calculated in each time period with respect to the percentage of progress, and the breakdown of costs is calculated as the sum of direct costs associated with project activities in each executive mode within the time windows from the earliest start times to the latest starts time of activities so that the activities can be scheduled according to their cost-based priorities in their permissible time windows known as total floats. The second portion of the costs including indirect costs are calculated on a daily basis Eq. (1):

$$Max(NPV) = \sum_{i=1}^{n}\sum_{m=1}^{M}\sum_{t=ES_i}^{LS_i} Pa_{imt}x_{imt}e^{-\alpha t} - \sum_{i=1}^{n}\sum_{m=1}^{M}\sum_{t=ES_i}^{LS_i} C_{imt}x_{imt}e^{-\alpha t} - \sum_{t=1}^{T} S_n C_{in} e^{-\alpha t}. \tag{1}$$

3.1.3.2 Minimization of Resource Usage Fluctuation

The objective function is considered as the sum of the absolute values of the deviations of resource consumption levels from the average resource consumption during the implementation of the project for each renewable resource Eq. (2):

$$Min(R_{dev}) = \sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{m=1}^{M} h\left|(r_k(t) - \bar{r}_k)\right|,$$
$$\bar{r}_k = \frac{1}{T}\sum_{t=1}^{T} r_k(t). \tag{2}$$

3.1.3.3 Constraints

$$\sum_{m=1}^{M}\sum_{t=ES_i}^{LS_i} x_{imt} = 1 \quad \forall i \in \{1,\ldots,n\} \tag{3}$$

$$\sum_{m=1}^{M}\sum_{t=ES_i}^{LS_i} tx_{imt} \le \sum_{m=1}^{M}\sum_{t=ES_j}^{LS_j} (t - d_{jm})x_{jmt} \quad \forall i \in P_j \quad \forall (i,j) \in A \tag{4}$$

$$\sum_{i=1}^{n}\sum_{m=1}^{M|}\sum_{q=t}^{t+d_{im}-1} r_{imk}x_{imq} \le R_k \quad \forall k \in \{1,\ldots,K\} \quad \forall t \in \{ES_i,\ldots,LS_i\} \tag{5}$$

$$\sum_{m=1}^{M}\sum_{t=ES_n}^{LS_n} tx_{nmt} \le DL \tag{6}$$

$$x_{imt} \in \{0,1\}$$
$$R_k \ge 0$$
$$\forall m \in \{1,\ldots,M\}, \forall i \in \{1,\ldots,n\}, \forall k \in \{1,\ldots,K\} \tag{7}$$

Equation (3) mandates that each activity must be executed in one execution mode only. Eq. (4) represents the precedence relationship with zero time lag between two activities so that an activity cannot be started unless its predecessor activity has been finished. Eq. (5) states that the total usage of any renewable resource at any time period must be equal or less than its available amount. Eq. (6) dictates that the project must be accomplished before its predetermined deadline. Finally, Eq. (7) defines the decision variables, indices and parameters of the model.

Given the uncertainty of the cost parameters (due to the factors such as inflation, economic and political sanctions, shortage of raw materials and labor changes) and the time parameters (due to the factors such as rework, supplier delays, transport delays, and unfavorable weather conditions), considering a deterministic number is inappropriate. In other words, a range of changes should be considered to estimate these parameters in the time-cost trade-off problem, and its variability should be incorporated into the model.

3.2 Robust Optimization Model

In order to deal with uncertainties in project scheduling, fuzzy, probabilistic, or robust approaches are generally used. The fuzzy scheduling method is used when there is no probability distribution function for activity cost and duration. This approach is typically applied to unique and new projects in which information from past similar projects is not available and the durations and costs of activities are determined based on the opinions of experts. In the probabilistic scheduling method, scenarios with different probabilities are assumed to consider uncertain parameters. However, knowing the exact distribution of the uncertain parameters is practically difficult in construction projects because of poor documentation. In such circumstances, it is advisable to use robust scheduling. The robust scheduling offers a distinguished approach to deal with uncertainties. This approach mitigates the negative impacts of uncertainties on project duartion and cost and increases the robustness of project schedule (Herroelen and Leus, 2005). Thus, in this study, the robust scheduling method is employed to tackle the uncertainties. The robust optimization approach aims to generate reliable optimal solutions that are not changing with the variations of the uncertain parameters. The proposed robust model takes the uncertain parameters of project cost and time into account.

In order to reduce the risk of decision-making and deal with the uncertainties of some parameters, the nominal model is initially presented for the problem in hand. Subsequently, the robust counterpart of the model is developed using the method introduced by Bertsimas and Sim (2004) so that the solutions are feasible and close to optimal even in the worst-case scenarios. In addition, due to a lack of knowledge of the probability distribution functions of some parameters, these types of parameters are considered as swing-random numbers in the symmetric range. A mixed-integer programming model is presented for the problem. The final linear robust model is developed as follows:

$$Max(NPV) = \sum_{i=1}^{n}\sum_{m=1}^{M}\sum_{t=ES_i}^{LS_i} Pa_{imt}x_{imt}e^{-\alpha t} - \sum_{i=1}^{n}\sum_{m=1}^{M}\sum_{t=ES_i}^{LS_i} C_{imt}x_{imt}e^{-\alpha t} - \sum_{t=1}^{T} S_n C_{in} e^{-\alpha t} - Z_0\Gamma_0 - \sum_{i=1}^{n}\sum_{m=1}^{M}\sum_{t=ES_i}^{LS_i} P_{imt}e^{-\alpha t} \tag{8}$$

$$Min(R_{dev}) = \sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{m=1}^{M} h\left|(r_k(t) - \bar{r}_k)\right| \qquad \bar{r}_k = \frac{1}{T}\sum_{t=1}^{T} r_k(t) \tag{9}$$

$$\sum_{m=1}^{M}\sum_{t=ES_i}^{LS_i} x_{imt} = 1 \qquad \forall i \in \{1,...,n\} \tag{10}$$

$$\sum_{m=1}^{M}\sum_{t=ES_i}^{LS_i} tx_{imt} - \sum_{m=1}^{M}\sum_{t=ES_j}^{LS_j}(t-d_{jm})x_{jmt} - Z_1\Gamma_1 - \sum_{m=1}^{M}\sum_{t=ES_j}^{LS_j} q_{jm} \le 0 \qquad \forall i \in P_j \quad \forall (i,j) \in A \tag{11}$$

$$Z_0 + p_{imt} \ge e_{imt}x_{imt} \qquad \forall m \in \{1,...,M\}, \forall i \in \{1,...,n\}, \forall t \in \{ES_i,...,LS_i\} \tag{12}$$

$$Z_1 + q_{jm} \ge \tilde{d}_{jm}y_{jm} \qquad \forall m \in \{1,...,M\}, \forall j \in \{1,...,n\} \tag{13}$$

$$\sum_{i=1}^{n}\sum_{m=1}^{M|}\sum_{q=t}^{t+d_{im}-1} r_{imk}x_{imq} \le R_k \qquad \forall k \in \{1,...,K\} \quad \forall t \in \{ES_i,...,LS_i\} \tag{14}$$

$$\sum_{m=1}^{M}\sum_{t=ES_n}^{LS_n} tx_{nmt} \le DL \tag{15}$$

$$\begin{aligned} & x_{imt} \in \{0,1\} \\ & R_k \ge 0 \\ & p_{imt} \ge 0 \\ & q_{jm} \ge 0 \\ & Z_0, Z_1 \ge 0 \\ & \forall m \in \{1,...,M\}, \forall i \in \{1,...,n\}, \forall k \in \{1,...,K\} \end{aligned} \tag{16}$$

where Z_0, p_{imt}, and x_{imt} are the robust variables added to the nominal model for the uncertain cost parameter (c_{imt}). Also, Z_1, q_{jm}, y_{jm} are the dual variables added to the nominal model for the uncertain parameter of the duration of each activity (d_{jm}).

Uncertain parameters of the cost associated with each activity are defined in the interval [c_{imt}, $c_{imt} + e_{imt}$] where $e_{imt} \ge 0$. Indeed, e_{imt} includes the positive deviations of costs with the aim of minimizing the maximum cost amount. In other words, minimization takes place in the worst-case scenario. The nominal cost of each activity (c_{imt}) is the most likely amount of activity cost that is determined by the project manager or decision-makers. Γ_0 is the protection Level of objective function whose number of values can be equal to the number of uncertain parameters of the model. Z_1 is the rate of change in the protection function related to the cost objective function for each unit of change in the amount of Γ_0. p_{imt} is also the rate of change in the protection function related to the cost objective function, which is defined as the change in the cost tolerance of activity *i*.

Similarly, the uncertain parameters of time associated with each activity are defined in the interval $[d_{im}, d_{im}+\hat{d}_{im}]$, which has symmetrical distribution of positive and negative deviations of activity duration. The nominal amount of time for each activity (d_{im}) is the most probable amount of time for each activity, and $\hat{d}_{im}$ is the range of time changes of each activity. Parameter Γ_1 is the value of conservatism level of the precedence constraint, including the uncertain parameter of activity duration.

3.3 Lexicographic Goal Programming (LGP) Method

A multi-objective model should first be transformed into a single-objective model in order to be solved by an exact method. Therefore, the lexicographic goal programming (LGP) method is used in this study.

LGP was introduced by Lee in 1972. This technique, which is one of the goal programming (GP) methods which has been used successfully in solving many multi-objective optimization and scheduling problems. In this method, a target level is first defined for each objective function, deviational variables are then defined to show deviations from target levels. Finally, the multi-objective model is transformed into a single-objective problem using the approach of minimizing deviations of objective functions from target levels.

Equations (8) to (10) represent the nominal LGP model:

$$Lex\ Min\ a=U_1 d_1'^{-}+U_2 d_2^{+} \tag{17}$$

$$Max(NPV)=\sum_{i=1}^{m}\sum_{m=1}^{M_i}\sum_{t=ES_i}^{SL_i} Pa_{imt}X_{imt}e^{-\alpha t}-\sum_{i=1}^{m}\sum_{m=1}^{M_i}\sum_{t=ES_i}^{SL_i} C_{imt}X_{imt}e^{-\alpha t}$$

$$-\sum_{t=1}^{T} S_n C_{in} e^{-\alpha t}-d_1^{+}+d_1'^{-}=F^1(x)^{*} \tag{18}$$

$$Min(R_{dev})=\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{m=1}^{M} h|r_k(t)-\bar{r}_k|-d_2^{+}+d_2'^{-}=F^2(x)^{*} \tag{19}$$

Equations (11) to (13) show the uncertain LGP model.

$$Lex\ Min\ a=U_1 d_1'^{-}+U_2 d_2^{+} \tag{20}$$

$$Max(NPV)=\sum_{i=1}^{n}\sum_{m=1}^{M_i}\sum_{t=ES_i}^{LS_i} Pa_{imt}X_{imt}e^{-\alpha t}-\sum_{i=1}^{n}\sum_{m=1}^{M_i}\sum_{t=ES_i}^{LS_i} C_{imt}X_{imt}e^{-\alpha t}$$

$$-\sum_{t=1}^{T} S_n C_{in} e^{-\alpha t}-Z_0\Gamma_0-\sum_{i=1}^{n}\sum_{m=1}^{M_i}\sum_{t=ES_i}^{LS_i} P_{imt}e^{-\alpha t}-d_1^{+}+d_1'^{-}=F'^1(x)^{*} \tag{21}$$

$$Min(R_{dev})=\sum_{k=1}^{K}\sum_{t=1}^{T}\sum_{m=1}^{M} h|r_k(t)-\bar{r}_k|-d_2^{+}+d_2'^{-}=F'^2(x)^{*} \tag{22}$$

where $F^1(x)^*$ and $F^2(x)^*$ are the ideal values of each of the objective functions that are obtained by considering the single-objective model. Also, d_1^+ and $d_1'^-$ are respectively positive deviation variable of over-achievement of ideal objective value and negative deviation variable of under-achievement of ideal objective value of ideal values in the first objective function, and variables d_2^+ and $d_2'^-$ are the positive and negative deviation variables of the ideal values in the second objective function.

4. Case Study

A network of ten activities of a hypothetical project is considered to solve the proposed robust model shown in Fig. 2. The characteristics of the project are given in Table 3. Activities 0 and 11 are the dummy activities corresponding with the start and finish of the project.

There are uncertain parameters in the objective functions and constraints of the general form of the proposed model. In the robust optimization method, all uncertain parameters are determined in the worst-case scenario to reduce deficiency and

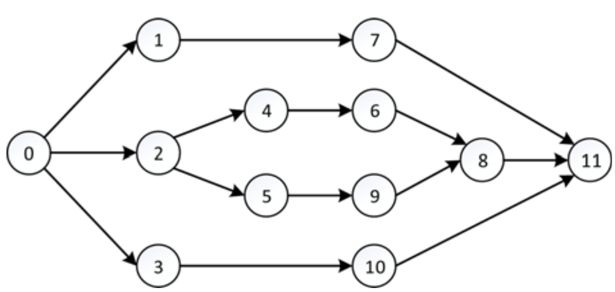


Fig. 2. Project Network

Table 3. Project Characteristics

i	m_i	d_{mi}	r_{imk}	i	m_i	d_{mi}	r_{imk}
0	1	0	0	6	1	1	1
1	1	4	3		2	3	1
	2	5	2	7	1	1	3
2	1	1	3		2	3	2
	2	2	2	8	1	1	3
3	1	1	2		2	2	3
	2	2	1	9	1	3	4
4	1	2	5		2	1	1
	2	3	4	10	1	2	2
5	1	2	4		2	1	3
	2	5	3	11	1	0	0

risks. As a result, the positive deviations of the distribution of uncertain parameters are considered for solving the model. To determine the number of robust model variables, three robust variables (Z_0, q_{imt}, x_{imt}) for the uncertain parameter C_{imt} and three robust variables (Z_1, p_{jm}, y_{jm}) for the uncertain parameter d_{jm} are added to the model. Therefore, the number of variables of the robust counterpart model is calculated as follows:

[Number of uncertain parameters × 3] + [Number of crisp model variables] = [Number of robust model variables]

4.1 Results

The lexicographic goal programming (LGP) model consists of two objective functions, 873 variables, and 475 constraints, which are represented in Table 4.

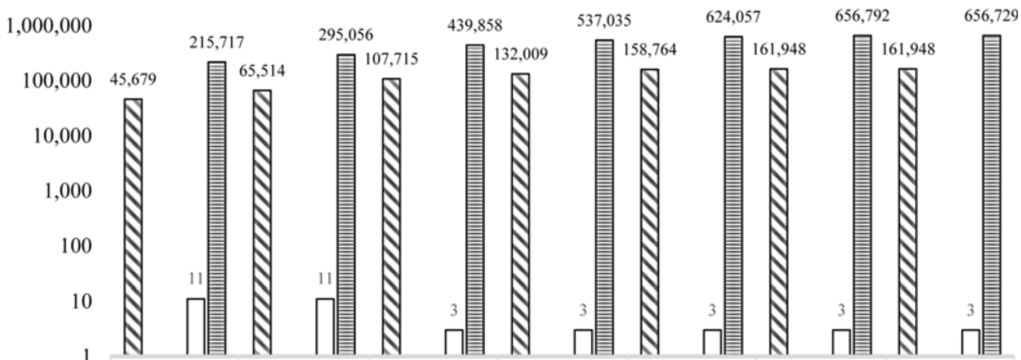
The main parameters of the model include the resources required for performing each activity in each execution mode, payments, direct costs related to the execution of each activity in each time period and indirect daily costs. In addition, uncertain parameters of the model contain the durations of activities and project costs, which can be quantified in the range of nominal values and positive deviations from their nominal values. The range $[C_{imt}, C_{imt} + e_{imt}]$ is considered for the project costs and the range $[d_{im}, d_{im} + \hat{d}_{im}]$ is considered for activity durations with a fluctuation of 20% of the nominal values, all of which are generated and tested with 10,000 times of Monte Carlo simulation

Table 4. Type and Number of the Variables and Constraints of the Proposed Model

Describe	Type	Number
Variables	Main	431
	Robust	442
	Deviation from the goal	2
	Total	875
Constraints	Main	55
	Robust	475
	Goal	2
	Total	532

Table 5. The Values of Deviation from the Objective Functions of the Robust Model in Different Scenarios of the Protection Level

Γ_0, Γ_1	0,0	1,1	3,3	5,5	7,7	9,9	10,10
d_1^-	45.679	65.514	107.715	132.009	158.764	161.948	161.948
$d_1'^+$	0	0	0	0	0	0	0
d_2^+	0	0	0	0	0	0	0
$d_2'^+$	11	11	3	3	3	3	3
Objective Function	215.717	295.056	439.858	537.035	624.057	656.792	656.729



(Γ0 ,Γ1)	(0,0)	(1,1)	(3,3)	(5,5)	(7,7)	(9,9)	(10,10)
d1-	45,679	65,514	107,715	132,009	158,764	161,948	161,948
d1'+	0	0	0	0	0	0	0
d2+	0	0	0	0	0	0	0
d2'+	11	11	3	3	3	3	3
objective value	215,717	295,056	439,858	537,035	624,057	656,792	656,729

Fig. 3. The Deviations from the Objective Functions of the Robust Model in Different Scenarios of the Protection Level

with three normal, uniform, and triangular distribution functions. The ideal values of the first and second objective functions are calculated for the robust model by separately solving the original model with each of the objective functions and the constraints, which are equal to $f_1 = 1615.04$ and $f_2 = 5$.

To examine the effect of changes in protection levels in the model and sensitivity analysis of these parameters on the objective function, the model is solved once for each change in conservation levels. Due to the broadness of uncertain parameters and time-consuming calculations, limited number of protection levels should be taken into consideration. The results of solving the model with GAMS software for different values of conservation levels are presented in Table 5. Fig. 3. depicts the deviations from the objective functions of the robust model in different scenarios of the protection level.

The first column of Table 5 represents a crisp model considering the zero conservatism level and indicates no fluctuation, and the last column shows the maximum fluctuations, which is the most possible conservative solution.

Robust models reduce the level of decision-making risks with increasing the level of conservatism. The above results illustrate the capability of the proposed model regarding the uncertainty of the problem data. As can be seen, with increasing the level of

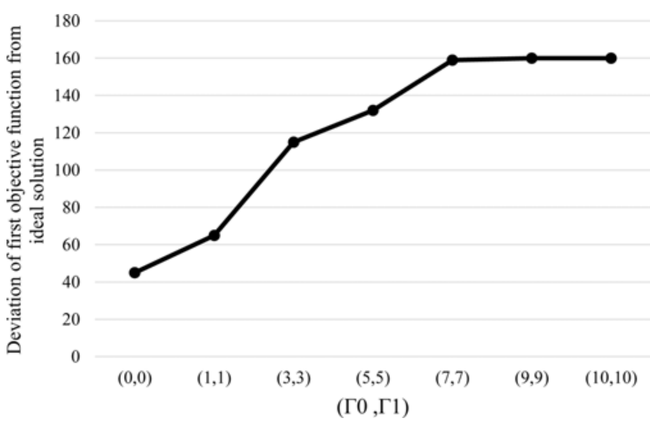


Fig. 4. Deviations of the First Objective Function-d_1

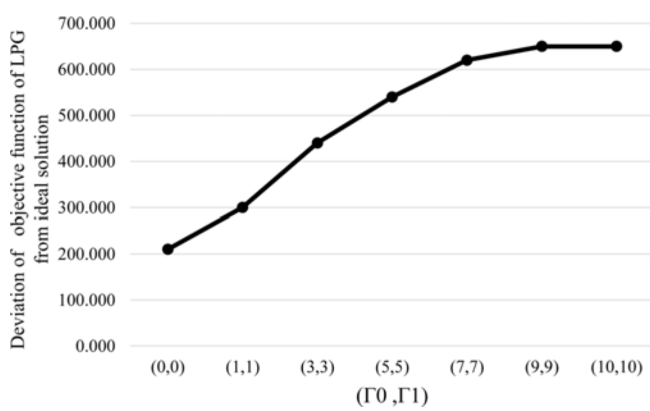


Fig. 5. Deviations of the Original Objective Function

conservatism Γ_0 and Γ_1, the deviations from the ideal values for the first objective function increase, and the deviations for the second objective function decrease and also the values of the original objective function increase (Figs. 4 and 5).

4.2 Monte Carlo Simulation

Subsequently, Monte Carlo simulation was used to examine the quality of the obtained solutions of the robust model. The sensitivity analysis of the nominal model was performed by considering constant values for the variables of the crisp model. Tables 6 to 8 represent 10,000 times of the model simulation with uncertain parameters with normal, uniform, and triangular distribution functions. Considering the average of simulation results and the expectation indices, standard deviation, maximum and minimum values of the objective function, the sensitivity of the model to the variability of the uncertain parameters is evaluated. Also, due to the uncertainty of the constraints, there is a possibility that the solutions to the problem may be infeasible in relation to the random values generated. As a result, the percentage of violating constraints is calculated for each observation (Shown in Fig. 6).

Table 6. Results of 10,000 Monte Carlo Simulations for Protection Levels with Normal Distribution

Γ_0, Γ_1	Mean (R(x))	Var (R(x))	Min (R(x))	Max (R(x))	Percentage of violating constraints
(0,0)	355.24	14.53	350.86	359.63	0.98
(1,1)	378.59	13.53	371.63	385.55	0.58
(3,3)	457.135	10.43	449.62	464.65	0.14
(5,5)	549.60	8.49	540.64	558.56	0.11
(7,7)	658.08	8.42	640.62	675.55	0.04
(9,9)	666.86	7.34	657.75	667.98	0
(10,10)	665.04	7.34	660.54	669.54	0

Table 7. Results of 10,000 Monte Carlo Simulations for Any Protection Levels with Uniform Distribution

Γ_0, Γ_1	Mean (R(x))	Var (R(x))	Min (R(x))	Max (R(x))	Percentage of violating constraints
(0,0)	345.94	14.34	338.43	353.45	1
(1,1)	357.98	12.31	351.43	364.53	0.50
(3,3)	369.42	11.24	360.43	378.42	0.13
(5,5)	426.385	8.30	416.34	436.43	0.03
(7,7)	439.97	8.23	434.32	445.63	0.003
(9,9)	505.83	7.23	491.35	520.31	0
(10,10)	505.99	7.03	491.43	521.23	0

Table 8. Results of 10,000 Monte Carlo Simulations for Any Protection Levels with a Triangular Distribution

Γ_0, Γ_1	Mean (R(x))	Var (R(x))	Min (R(x))	Max (R(x))	Percentage of violating constraints
(0,0)	332.77	14.20	325.23	340.32	1
(1,1)	360.32	11.98	348.32	360.32	0.98
(3,3)	410.78	10.31	402.34	416.23	0.54
(5,5)	420.88	7.31	412.34	429.43	0.14
(7,7)	443.27	6.23	427.25	443.27	0.12
(9,9)	487.30	6.02	479.29	495.37	0.03
(10,10)	487.09	6.015	478.32	495.87	0

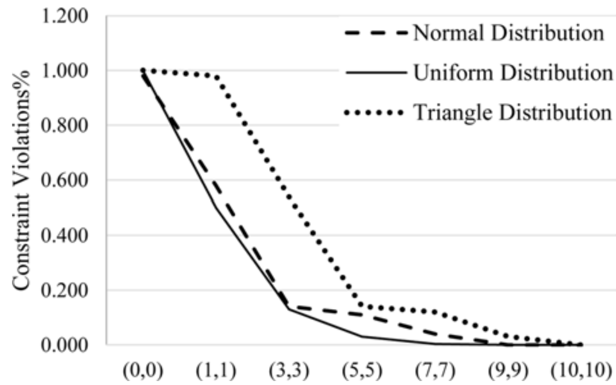


Fig. 6. Analysis of Results Obtained from Monte Carlo Simulation

Examining the obtained results from the data simulation at different protection levels shows that the percentage of constraint violation has decreased with increasing the protection levels. Also, it can be seen that the amount of standard deviation has declined with increasing the protection levels, indicating an increase in the robustness of the proposed model against uncertain parameters.

Comparisons show that the results of the robust model have much worse solutions than the crisp model. The reason is that all uncertain parameters are determined based on the worst possible scenario in the robust optimization to reduce deficiency and risks. As the level of uncertainty in the proposed model increases, worse answers are generated and the decision becomes much more sensitive and rigorous. This rigor yields a solution in the robust optimization model that decreases the probability of failure comparing to the crisp model. Moreover, the preference of solutions corresponding with different distribution functions indicates the robustness of the model against the variations of the uncertain parameters.

4.3 MOPSO and NSGAII Metaheuristic Algorithms

It is clear that the right choice of parameters has a significant impact on the performance of algorithms. There are several techniques for setting the parameters of a given algorithm. The method introduced by Clerc and Kennedy (2002) for setting the parameters of MOPSO algorithm is used in this paper. Clerc and Kennedy (2002) showed that the convergence of the PSO algorithm is strongly dependent on its main parameters including w, c_1 and c_2. In this regard, the following equation was presented to determine the parameters of this algorithm, which is applied in this study:

$$\gamma = \frac{2}{\phi_1 + \phi_2 - 2 + \sqrt{(\phi_1 + \phi_2)^2 - 4(\phi_1 + \phi_2)}}, \tag{23}$$

Table 9. Different Levels for Parameter Setting

Algorithm	Parameter	Range	Low (-1)	Medium (0)	High (+1)
NSGAII	Pop_size	100-300	100	200	300
	Pc	0.4-0.8	0.4	0.6	0.8
	Pm	0.2-0.4	0.2	0.3	0.4

Table 10. Experimental Tests for Parameter Setting

Run number	Parameter			Indices					Response Value
	POP-size	Pc	Pm	CPU-time	NPS	MID	S	MS	
1	-1	-1	-1	1.00	1.00	0.97	0.30	0.60	3.81
2	+1	-1	-1	0.39	0.73	0.98	0.12	0.81	3.02
3	-1	+1	-1	0.72	0.81	0.98	0.46	0.42	3.39
4	+1	+1	-1	0.28	0.53	0.99	0.46	0.32	2.57
5	-1	-1	+1	0.84	0.69	0.99	0.26	0.50	3.27
6	+1	-1	+1	0.33	0.64	0.98	0.44	0.56	2.97
7	-1	+1	+1	0.63	0.69	0.99	1.00	0.27	3.58
8	+1	+1	+1	0.24	0.80	0.99	0.32	0.51	2.86
9	-1	0	0	0.59	0.54	0.98	0.08	0.31	2.51
10	+1	0	0	0.31	0.66	0.99	0.41	0.33	2.70
11	0	-1	0	0.33	0.63	0.97	0.25	0.51	2.69
12	0	+1	0	0.38	0.66	0.99	0.66	0.29	2.98
13	0	0	-1	0.49	0.81	1.00	0.19	0.39	2.88
14	0	0	+1	0.41	0.92	1.00	0.57	0.36	3.25
15	0	0	0	0.45	0.53	0.99	0.62	0.33	2.92
16	0	0	0	0.45	0.81	0.99	0.57	0.34	3.16
17	0	0	0	0.25	0.57	1.00	0.10	1.00	2.91
18	0	0	0	0.45	0.69	1.00	0.10	0.63	2.87
19	0	0	0	0.44	0.66	1.00	0.47	0.30	2.87
20	0	0	0	0.45	0.80	1.00	0.25	0.46	2.95

$$c_1 = \gamma \times \phi_1 ,\ c_2 = \gamma \times \phi_2 ,\ w = \gamma,\ w = w \times w_{damp},$$

where $\phi_1 + \phi_2 > 4$, the best values are obtained, if $\phi_1 = \phi_2$ and $\phi_1 + \phi_2 = 4.1$. As a result, the parameters values are obtained as follows: $\gamma = 0.6$, $c_1 = 1.26$, $c_2 = 1.26$, $w = 0.6$.

In addition, the response surface methodology (RSM) is used for setting the parameters of NSGAII algorithm. For this purpose, three levels for the three main parameters of the algorithm are considered, which can be seen in Table 9.

Then, the relevant experiments were performed and the results were reported according to Table 10.

The results of variance analysis are displayed in Table 11. The value of *P* for the *linear* variable indicates that the parameters of *Pop-size*, *Pc* and *Pm* algorithms do not independently affect the performance of the algorithm, while this value in the *Square* and *interaction* variables confirms the interaction of these parameters on the performance of the algorithm.

Finally, the optimal level of the input parameters of the algorithm is determined using LINGO software and regression equation, which is shown in Table 12.

Table 11. Results of Variance Analysis of Parameter Setting

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	1.41751	1.41751	0.157501	2.3	0.106
Linear	3	0.65378	0.67839	0.226131	3.3	0.066
Square	3	0.53257	0.53257	0.177523	2.59	0.111
Interaction	3	0.23116	0.23116	0.077053	1.12	0.385
Residual Error	10	0.68576	0.6857	0.068576		
Lack-of-Fit	5	0.62796	0.62796	0.125593	1.087	
Pure Error	5	0.05779	0.05779	0.011559		
Total	19	2.10327				

Table 12. Optimal Values of the Parameters of NSGAII

	Parameter	Optimum value
NSGAII	Pop-size	300
	Pc	0.74
	Pm	0.27

4.4 Validation of the Proposed Algorithms

In order to compare the performance of the proposed algorithms and validation of the research method, these algorithms were implemented in the problem instances taken from the standard PSLIB library. For this purpose, 12, 10 and 8 examples were selected from problems with 10, 20 and 30 activities, respectively. Then, the NSGAII and MOPSO algorithms were run three times for each instance. The results are illustrated in Table 13 based on 5 indices of CPU computational time, number of Pareto solutions (NPS), Mean Ideal Distance (MID), Spacing (S), and Maximum Spread (MS) (Jolai et al., 2013; Zhang et al., 2020; Heidari et al., 2020).

First, the Kolmogorov-Smirnov test was used to check the normality of the data obtained from the implementation of the algorithms. The data are normal and the P-value is greater than 0.05, so the H_0 hypothesis is accepted at the 95% confidence level. Therefore, the parametric tests can be used to compare the algorithms. Subsequently, the paired *t* test is performed. In this test, the hypothesis zero means the equality of two algorithms based on each index and the opposite hypothesis expresses inequality of two algorithms. According to the test results and *Sig* values, the hypothesis of equality of the means of the CPU time, NPS, and MS indexes is not true for the two algorithms. In other words, MOPSO outperforms NSGA-II in terms of three indexes.

Subsequently, the proposed model is implemented on a real-world construction project (34 activities), which is the design, procurement, construction, transportation, installation, and commissioning of a wellhead platform project with the total value of 43,442,000 Euros and the duration of 36 months. In this study, considering the project's installation and commissioning phase, we seek to find a suitable project schedule to increase the contractor's profit. In addition, the resource leveling objective is taken into account due to the high cost of leasing the required machinery and equipment. The information of the project

Table 13. Results of PSLIB Examples

	J10					J20					J30				
Algorithm	CPU time	NPS	MID	S	MS	CPU time	NPS	MID	S	MS	CPU time	NPS	MID	S	MS
NSGA||	2,411	2	1997	9	2	3,370	3	1958	11	12	4,313	8	1875	2	50
MOPSO	1,075	6	1889	3	33	620	5	1953	11	12	1,376	7	1803	3	50
NSGA||	2,029	3	1708	15	4	3,172	10	1663	15	12	4,727	9	1802	4	51
MOPSO	1,138	7	1687	10	22	799	5	1971	15	43	1,492	7	1833	4	62
NSGA||	1,559	3	1740	8	2	3,207	9	1600	7	17	4,718	12	1810	3	67
MOPSO	1,094	9	1105	2	37	799	12	1876	9	53	1,502	14	1875	5	56
NSGA||	1,816	2	1531	12	3	3,169	8	1536	20	14	4,719	12	1832	3	58
MOPSO	1,132	11	1047	6	25	800	10	1922	12	18	1,501	13	1804	3	59
NSGA||	1,988	7	1922	11	8	3,274	10	1703	19	16	4,672	9	1875	5	50
MOPSO	1,061	14	1808	8	38	813	11	1949	15	17	1,532	16	1868	5	56
NSGA||	1,954	9	1742	13	6	3,362	6	1118	6	13	4615	9	1831	4	58
MOPSO	1,092	8	1498	9	25	796	9	1951	13	21	1,410	15	1846	3	49
NSGA||	1,916	10	1732	13	5	3,281	6	1793	5	29	4,619	9	1881	4	63
MOPSO	1,150	11	1338	3	44	854	11	1956	11	15	1,521	14	1894	6	51
NSGA||	1,498	4	1920	9	3	3,109	4	1684	4	18	4,791	13	1853	4	57
MOPSO	1,156	8	1333	8	37	821	14	1972	10	12	1,390	12	1772	4	63
NSGA||	2,126	7	1682	9	6	3,281	9	1631	9	20					
MOPSO	1,159	14	1200	4	31	846	5	1847	14	19					
NSGA||	1,605	7	1643	15	5	3,342	6	1546	12	24					
MOPSO	1,184	10	1274	3	24	816	8	1920	12	20					
NSGA||	1,823	3	1558	11	9										
MOPSO	1,091	15	1612	10	35										
NSGA||	1,673	6	1848	13	2										
MOPSO	1,173	13	1505	9	37										

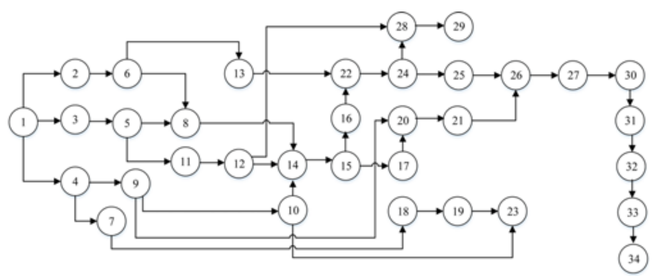


Fig. 7. Network Project (34 activity)

Table 14. Results Obtained from Using the MOPSO and NSGA-II Algorithms in a Case Study

Algorithm	NPV	R_{dev}	CPU Time
NSGA-II	19,411,422	143	617.3
MOPSO	23,494,593	126	1234.4

Table 15. Control Parameters of NSGA-II Algorithm

Control parameters	Values
Maximum Number Of Iterations	200
Population Size	300
Crossover Percent	0.74
Mutation Percent	0.27
Stopping Rule	200 Repeat

Table 16. Control Parameters of MOPSO Algorithm

Control parameters	Values
Maximum Number Of Iterations	200
Population Size	300
Repository Size	100
Personal Learning Coefficient (c_1)	1
Global Learning Coefficient (c_2)	2
Number Of Grids Per Dimension	5
Stopping Rule	200 Repeat

activities is provided in Fig. 7 and Appendix I.

The results were obtained by implementing the MOPSO and NSGA-II metaheuristic algorithms considering the uncertain parameters of cost and duration of activities and 20% fluctuation of the nominal values (Table 14). Also, the amounts of the parameters of the algorithms are presented in Tables 15 and 16.

The achieved results indicate the robustness of the proposed model against uncertainties of the parameters. Besides, the profit and resource distribution level during the project horizon significantly improved comparing to the baseline project schedule. This robust scheduling model assists project managers with making real time decisions based on the existing conditions and circumstances of projects during the planning phases of projects by adjusting the protection levels in the proposed model according to the number and importance of project risks.

4.5 Practical Implications

In any construction project, several factors such as time and cost are of significant importance for various stakeholders such as contractors. The cost and duration of each project activity vary corresponding with each execution mode. On the other hand, the contractors attempt to complete the projects in shorter durations with higher profits and return on investment. In addition, contractors pay more attention to evenly distribution of resource usage during the entire project horizon in order to reduce the costs as well as the negative consequences of hiring and firing human resources. In other words, balancing the two objective functions of maximizing net present value of the project and minimizing fluctuations in resource usage is a major challenging problem in the field of project management from the contractor's point of view. Therefore, the proposed bi-objective optimization model can help the contractors' project managers cope with this problem.

5. Conclusions

Given the high importance of financial resources in the implementation of construction projects, the project scheduling model with the goal of profit maximization considering discounted cash flows of the project was investigated in this research. Past studies on project cash flows have considered the costs of the execution of activities regardless of the resources used in projects. However, the allocation and distribution of resources during the project implementation phase greatly influence the additional costs of projects. Therefore, in this study, the objective function of minimizing the fluctuations of the resource consumption level known as resource leveling was considered as the second objective function. Also, the assumptions related to the real-world projects regarding multi-mode activities, limitation of renewable resources, and the deadline of project were incorporated into the proposed model to make it more efficient. Moreover, a robust scheduling method was presented in this study to better deal with project uncertainties regarding cost and time.

The proposed model was implemented in a sample project with ten activities and solved using lexicographic goal programming (LGP) method and GAMS software. The main parameters of the model include the resources required to perform each activity in each execution mode, payments, direct costs related to the execution of each activity in each time period and indirect daily costs. As the conservation levels increase, the amount of deviation from the ideal value of the first objective function increases and the amount of deviation from the ideal value of the second objective function decreases. In addition, the sensitivity analysis of the proposed robust model is performed considering different conservation levels, and the results are evaluated by Monte Carlo simulation with three normal, uniform and triangular distributions.

The results obtained from the simulation observations at different protection levels revealed that increasing the protection levels decreases the percentage of constraint violation. Also, increasing protection levels leads to increasing the mean of the obtained results and decreasing the standard deviation, which indicates the robustness of the proposed model against the variations of the uncertain parameters. Due to the NP-hardness of the problem in hand, the exact methods are not able to find the optimal solutions for the large-sized problems. Hence, two well-known metaheuristic algorithms named NSGA-II and MOPSO were exploited to solve the problem. The bi-objective model was implemented in 30 problem instances with different sizes, and solved by using the NSGA-II and MOPSO algorithms.

The findings of two algorithms were compared in terms of five indices including CPU computational time, number of Pareto solutions (NPS), Mean Ideal Distance (MID), Spacing (S), and Maximum Spread (MS). The results demonstrated the high performance of the two algorithms in solving the problem and the better performance of MOPSO compared with NSGA-II based on three indices of CPU computational time, number of Pareto solutions (NPS), and Maximum Spread (MS). Finally, the proposed model was implemented in an offshore equipment installation phase of a wellhead platform project with 34 activities. Uncertain parameters of the model include the durations of activities and project costs, which are set in the range of their nominal values and the positive deviations of 20% from their nominal values. The findings demonstrate that the robustness of the model against the variations of uncertain parameters. In addition, the project profit and the even distribution level of resources throughout the project horizon significantly improved compared to the initial schedule baseline. The proposed model assists project managers with making the best decisions with adjusting the protection levels based on the project risks.

As some suggestions for future research, the other objective functions such as minimizing project duration can be considered in the model. Also, other precedence relationships and maximum time lag between activities may be taken into account. Moreover, the chance constraint method may be applied to transform the non-deterministic model into the deterministic model. Furthermore, Benders decomposition method can be employed to solve the model.

Due to model simplification, finish-to-start precedence relationship together with zero time lag was considered. In addition, difficulties in calculating and estimating the duration, cost and required resources in each activity execution mode can be stated as some of the limitations of the present research. As some suggestions for further studies, the proposed model should be applied to other construction projects. Also, other objective functions such as minimization of environmental impacts of project activities or maximizing project quality level should be incorporated into the model. Moreover, other types of activity precedence relationships can be taken into consideration. Furthermore, other metaheuristic algorithms may be used and the results be compared.

Acknowledgments

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Appendix I. One-Sample Kolmogorov-Smirnov Test (NSGA-II and MOPSO Algorithms)

One-Sample Kolmogorov-Smirnov Test (NSGA-II)

		CPU.Time	NPS	MID	S	DM
N		30	30	30	30	30
Normal Parameters[a]	Mean	3071.3000	7.1667	1733.8000	9.1667	22.8000
	Std. Deviation	1153.66705	3.09709	174.76356	4.90660	22.04447
Most Extreme Differences	Absolute	.160	.156	.099	.135	.220
	Positive	.160	.113	.074	.135	.220
	Negative	-.143	-.156	-.099	-.079	-.173
Kolmogorov-Smirnov Z		.878	.857	.544	.742	1.202
Asymp. Sig. (2-tailed)		.423	.455	.929	.641	.111

One-Sample Kolmogorov-Smirnov Test (MOPSO)

		CPU.Time	NPS	MID	S	DM
N		30	30	30	30	30
Normal Parameters	Mean	1106.4333	10.4667	1737.0667	7.6667	35.4667
	Std. Deviation	267.89610	3.32942	237.90377	4.07121	15.96274
Most Extreme Differences	Absolute	.160	.122	.242	.149	.144
	Positive	.160	.104	.162	.149	.144
	Negative	-.110	-.122	-.242	-.095	-.102
Kolmogorov-Smirnov Z		.878	.670	1.328	.819	.789
Asymp. Sig. (2-tailed)		.424	.760	.059	.514	.563

Appendix II. Independent Samples Test (NSGA-II and MOPSO Algorithms)

		Levenes Test for Variances		t-test for Equality of Means						
									95% Confidence Interval of the Difference	
		F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
CPU Time	Equal variances assumed	42.735	.000	9.087	58	.000	1964.86667	216.23413	1532.02703	2397.70631
	Equal variances not assumed			9.087	32.118	.000	1964.86667	216.23413	1524.47585	2405.25748
NPS	Equal variances assumed	.391	.534	-3.975	58	.000	-3.30000	.83020	-4.96183	-1.63817
	Equal variances not assumed			-3.975	57.699	.000	-3.30000	.83020	-4.96201	-1.63799
MID	Equal variances assumed	4.810	.032	-.061	58	.952	-3.26667	53.89512	-111.14946	104.61613
	Equal variances not assumed			-.061	53.240	.952	-3.26667	53.89512	-111.35521	104.82187
S	Equal variances assumed	.710	.403	1.289	58	.203	1.50000	1.16404	-.83007	3.83007
	Equal variances not assumed			1.289	56.091	.203	1.50000	1.16404	-.83176	3.83176
DM	Equal variances assumed	3.982	.051	-2.549	58	.013	-12.66667	4.96913	-22.61346	-2.71987
	Equal variances not assumed			-2.549	52.854	.014	-12.66667	4.96913	-22.63412	-2.69921

Appendix III. Research Data (34 activities)

Costs	Incomes	Resources		Predecessor activities	Duration	Activity
0	1,386,600	40	79	-	10	1
5,018,700	4,455,805	97	75	1	10	2
2,064,630	1,267,529	56	79	1	120	3
3,520,594	3,829,175	75	35	1	20	4
1,351,122	4,691,367	42	46	3	14	5
3,914,653	5,439,430	79	72	2	0	6
2,437,308	4,111,432	36	28	4	20	7
724,591	5,361,361	70	80	5-6	10	8
5,193,773	5,285,261	62	44	4	20	9
4,770,114	1,286,397	64	97	14	10	10
2,963,163	2,720,448	32	77	5	19	11
4,000,137	1,703,190	95	45	11	9	12
2,186,066	5,422,164	96	62	6	14	13
4,070,978	2,995,298	22	24	8-10-12	9	14
2,652,430	4,799,856	36	26	14	4	15
3,232,525	2,879,090	65	32	15	4	16
3,106,440	5,511,768	25	71	15	4	17

Costs	Incomes	Resources		Predecessor activities	Duration	Activity
1,942,808	3,979,180	59	24	7	1	18
2,805,747	1,959,410	80	52	18	2	19
3,477,708	523,852	98	94	9-17	0	20
1,099,272	3,241,122	69	40	20	2	21
3,552,227	5,090,630	40	88	13-16	1	22
905,330	2,931,904	48	73	10-19	1	23
5,474,744	612,996	35	68	22	1	24
445,920	3,923,058	82	32	24	2	25
24,949	3,676,934	83	57	21-25	0	26
1,475,463	5,522,185	93	40	26	2	27
3,201,801	746,454	85	53	12-24	1	28
2,957,450	400,407	78	81	28	1	29
1,907,805	482,879	96	75	27	2	30
2,726,745	50,350	59	32	30	0	31
6,255,285	563,993	52	54	31	2	32
2,813	3,300,179	48	34	32	1	33
867,573	4,458,805	90	43	33	1	34