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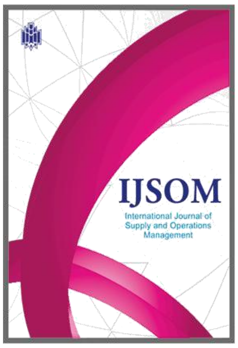

Multi-objective Optimization of Multi-mode Resource-constrained Project Selection and Scheduling Problem Considering Resource Leveling and Time-varying Resource Usage

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Abstract

In this paper, a multi-objective mixed-integer programming model is developed to cope with the *multi-mode resource-constrained project* selection and scheduling problem, aiming to minimize the makespan, maximize the net present value of project cash flows, and minimize the fluctuation of renewable resource consumption between consecutive time periods. Moreover, activities are considered to be subject to generalized finish-to-start precedence relations, and time-varying resource usage between consecutive time periods. To assess the performance of the proposed model, 30 different-sized numerical examples are solved using goal programming, epsilon constraint, and augmented epsilon constraint methods. Afterward, Tukey test is used to statistically compare the solution methods. Moreover, VIKOR method is used to make an overall assessment of the solution methods. Statistical comparisons show that there is a significant difference between the mean of the resource leveling objective functions for all the solution methods. In other words, goal programming statistically outperforms other solution methods in terms of the resource leveling objective function. This is not the case for the other objective functions and CPU times. In addition, results of the VIKOR method indicate that the goal programming method outperforms the other solution methods. Hence, goal programming method is used to perform some sensitivity analyses with respect to the main parameters of the problem. Results show that by improving any of the parameters at least one objective function improves. However, due to the conflicting nature and the impact of weights of objective functions, in most cases, the trend are not constant to describe a general pattern.

Keywords: Project portfolio selection; multi-mode resource constrained project Sscheduling problem (MRCPSP); Multi-objective optimization, Resource leveling; time-varying resource consumption; Time value of money.

1. Introduction

Resource Constrained Project Scheduling Problem (RCPSP) is an important topic in the project management area, and recently has been investigated by many researchers and practitioners. This arises from the fact that real world projects include different features and assumptions, e.g. number of projects (one or more), type of required resources (renewable, nonrenewable, etc.), objectives (time-based, cost-based, quality-based, etc.), number of execution modes (single- vs. multi-mode), number of skills (single- vs. multi-skills) (Hartmann and Briskorn, 2010; Hartmann and Briskorn, 2021). **U**sually, project manager(s) schedule projects considering more than one objective, of which the most popular ones are time-based and cost-based objectives. These objectives are of conflicting nature. In many cases, project manager(s) may utilize additional resources to accelerate the completion of the project. By doing so, they make a compromise between the completion time and total cost of the project. This leads to the development of the time-cost tradeoff problem (TCTP) (Hafezalkotob, Hosseinpour, Moradi, & Khalili, 2017; Hochbaum, 2016). The development of Multi-Mode Resource-Constrained Project Scheduling Problem (MRCPSP) by Elmaghraby (1977) was an attempt to make a compromise between these important conflicting objectives in RCPSPs. In fact, MRCPSP is an advanced version of RCPSP, which

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adds the mode selection procedure to the basic RCPSP (Beşikci et al., 2014; Afshar-Nadjafi, 2014; Elloumi et al., 2017, Delgoshaei et al., 2018). An important issue for many organizations is that they should select a number of more preferred projects from a set of available candidates, and schedule the selected projects regarding their own specific limitations. In such cases, an integrated framework is needed to not only form a portfolio of projects, but also, schedule activities of the selected projects. Obviously, when both the above-mentioned problems are integrated, decision maker will face a much more complicated problem, compared to the situations where, decisions on project selection and project scheduling are made in a separate manner. One of the main concerns of project managers is to reduce the costs related to the fluctuations of resource utilization. This can be performed by adjusting the start time of the non-critical activities, while satisfying the precedence constraints of the activities without violating the prescribed project deadline (Kazemi and Davari-Ardakani, 2020).

This paper copes with an integrated project selection and scheduling problem in the presence of multiple execution modes and time-varying resource usage. In the problem under consideration, in addition to time-based and monetary objectives, a resource-leveling objective is considered. The remainder of this paper is organized as follows. In section 2, a literature review of the problem under consideration is presented. In section 3, a mixed integer programming formulation for the considered problem is proposed. In section 4, the multi-objective decision making (MODM) methods used to solve the mathematical model are introduced. In section 5, different numerical examples are solved, and the obtained results are analyzed and discussed. Finally, section 5 concludes the paper, and proposes some future research recommendations.

2. Literature review

This section provides an overview of important studies in the area of resource constrained project scheduling, in order to investigate the main characteristics of the problem under consideration regarding the efforts made by researchers.
The resource constrained project scheduling problem (RCPSP) aims to schedule the activities of a project considering precedence relations and resource limitations (Shariatmadari et al., 2017). Generally, RCPSPs can be investigated from several different viewpoints, such as objectives, resources, and other features of projects. Hence, there exists a wide range of studies on the basis of RCPSP in the literature (Chakrabortty et al., 2016).

Multi-mode resource constrained project scheduling problem (MRCPSP) is a special type of RCPSP, in which some/all activities may be executed by using more than one time/resource or time/cost combination (Nemati-Lafmejani et al. 2019). Elmaghraby (1977) was a pioneering researcher who allowed activities to be performed in several execution modes. Toffolo et al. (2015) minimized the sum of completion times for projects in a multi-mode multi-project resource constrained project scheduling problem. Khalili-Damghani et al. (2016) considered multiple modes and time lags in precedence networks of activities, and minimized both project cost and makespan, while maximizing the quality of performing activities. They proposed heuristic methods based on integer programming to solve the problem under consideration. Balouka et al. (2016) proposed a mathematical programming model to maximize the net present value of a project, allowing multiple execution modes for activities. Schnell and Hartl (2016) investigated the MRCPSP with generalized precedence relations (GPRs). Toffolo et al. (2016) studied a multi-project MRCPSP aiming to minimize the sum of completion times for projects as well as the makespan of the last project. Chakrabortty et al. (2016) dealt with an MRCPSP, allowing activities to be rescheduled after a resource disruption. The activities were considered to be resumed or restarted after any disruption. Leyman and Vanhoucke (2016) studied an MRCPSP with discounted cash flows and different payment models. Elloumi et al. (2017) investigated an MRCPSP under mode change disruption minimizing both makespan and a disruption measure. Zoraghi et al. (2017) dealt with the integration of the MRCPSP and the material ordering problem. Afshar-Nadjafi (2018) dealt with the preemptive multi-mode resource constrained project scheduling problem, in which when an interrupted activity is resumed, execution modes may change. García-Nieves et al. (2018) and García-Nieves et al. (2019) investigated an MRCPSP with generalized precedence relations, in which activities are divided into sub-activities. The limited mode changeability was allowed between sub-activities. Tirkolaee et al. (2019) tackled an MRCPSP aiming to optimize the net present value and the makespan concurrently. Gnägi et al. (2019) developed two new continuous-time assignment-based MILP models to deal with MRCPSPs. Nemati-Lafmejani et al. (2019) and Nemati-Lafmejani and Davari-Ardakani (2020) addressed both multi-mode resource constrained project scheduling and contractor selection problems in a unified manner. Chakrabortty et al. (2020) provided a fast near-optimum solution to the multi-mode resource-constrained project scheduling problems (MRCPSPs) considering both renewable and nonrenewable resource requirements. Turkgenci et al. (2020) discussed a preemptive multi-project MRCPSP, allowing mode switching while activities are executing.

In many real-world environments, both project selection and project scheduling problems are matters of crucial importance. In fact, decision makers sometimes are faced with a number of available projects, of which one/some should be selected and scheduled regarding limitations on availability of resources. Gutjahr et al. (2010) proposed an integrated project selection, scheduling and staffing problem considering dynamic competencies of the resources, time-dependent capacities as well as release time and deadlines. Their proposed model aimed at maximizing the values of the selected projects and the efficiency increase of the resources due to learning effects.

Tofighian and Naderi (2015) proposed an ant colony optimization algorithm to cope with the integrated project selection and scheduling problem, aiming to maximize the project profits, and minimize the variation of resource consumption between consecutive time periods. Shariatmadari et al. (2017) developed a mixed-integer programming model to cope with the project selection and scheduling problem, aiming to maximize the available cash at the end of the planning horizon. Kumar et al. (2018) proposed a zero-one integer programming model to deal with the project selection and scheduling problem aiming to maximize the expected profit of the project portfolio, taking into account two types of interdependencies, namely mutual exclusiveness and complementariness among projects. RezaHosseini et al. (2020) proposed a multi-objective mathematical model to cope with a project portfolio selection and scheduling problem considering sustainable utility, project splitting and the dependency relationship between some projects. Moomivand et al. (2020) presented a mathematical formulation, and adopted a genetic algorithm to deal with a multi-mode resource constrained project selection and scheduling problem considering the reinvestment strategy in a flexible time horizon.

The classical RCPSPs aim to minimize the makespan. In addition, several other time-based objectives have been proposed, e.g. In the projects with certain/uncertain cash flows, optimizing the net present value of the project may be a matter of particular importance for decision maker(s). To gain more information about this issue in case of single/multiple project(s), one can refer to Leyman and Vanhocke (2016), He et al. (2016), Leyman et al. (2019), Tirkolaee et al. (2019), Heidari-Fathian and Davari-Ardakani (2020). In many cases, controlling hiring and firing costs of renewable resources and/or establishment, set up and renting costs of nonrenewable resources are of crucial importance. Hence, those costs pertaining to variation of resource consumption between consecutive time periods should be minimized to make the projects affordable. Therefore, several studies in the literature have dealt with the resource leveling (RL) problem. For more information about this issue, one can refer to Coughlan et al. (2015), Atan and Eren (2018), Qiao and Li (2018), Li et al. (2018), Li and Dong (2018) and Kazemi and Davari-Ardakani (2020).

In the classical RCPSP, any activity requires a constant amount of available resources during the execution time. Hartmann (2013, 2015) discusses the case that the resource requests vary over time. Although this is an inseparable assumption of real-world projects, it has been infrequently considered in the research works conducted in the field of RCPSP. As examples of such an approach, one can refer to Zimmermann and Trautmann (2018) and Hosseinian et al. (2019). Table 1 summarizes the main features of the related studies in the literature.

Table 1. The main features of the related studies in the literature

Authors (year)	Multiple Projects	Multiple modes	Types of decisions		Resource-		Types of objective function(s)	Time-varying resource usage
			Selection	Scheduling	Renewable resource	Nonrenewable resource		
Hartmann (2013)	×	×	×	✓	✓	×	• Makespan	✓
Hartmann (2015)	×	×	×	✓	✓	×	• Makespan	✓
Coughlan et al. (2015)	×	✓	×	✓	✓	×	• Resource availability cost	×
Tofighian and Naderi (2015)	✓	×	✓	✓	✓	×	• Expected benefit • Resource usage variation	×
Toffolo et al. (2015)	✓	✓	×	✓	✓	✓	• Total completion times of projects	×
Khalili-Damghani et al. (2015)	×	✓	×	✓	×	✓	• Makespan • Total cost • Total quality index	×
Balouka et al. (2016)	×	✓	×	✓	✓	✓	• Project value	×
Schnell and Hartl (2016)	×	✓	×	✓	✓	✓	• Makespan	×
Chakrabortty et al. (2016)	×	✓	×	✓	✓	✓	• Makespan	×

Table 1. Continued

Authors (year)	Multiple Projects	Multiple modes	Types of decisions		Resource-		Types of objective function(s)	Time-varying resource usage
			Selection	Scheduling	Renewable resource	Nonrenewable resource		
Leyman and Vanhoucke (2016)	×	✓	×	✓	✓	✓	• NPV of the project	×
He et al. (2016)	×	✓	×	✓	×	✓	• Maximal cash flow gap	×
Elloumi et al. (2017)	×	✓	×	✓	✓	✓	• Makespan • Disruption	×
Zoraghi et al. (2017)	×	✓	×	✓	✓	✓	• Makespan • Robustness • Total cost	×
Shariatmadari et al. (2017)	✓	×	✓	✓	✓	✓	• Terminal cash balance	×
Kumar et al. (2018)	✓	×	✓	✓	✓	×	• Total expected benefit	×
Afshar-Nadjafi (2018)	×	✓	×	✓	✓	✓	• Makespan	×
García-Nieves et al. (2018)	×	✓	×	✓	✓	×	• Makespan • Tardiness	×
Atan and Eren (2018)	×	×	×	✓	✓	×	• Resource usage deviation	×
Qiao and Li (2018)	×	✓	×	✓	✓	×	• Some resource leveling objectives	×
Li et al. (2018)	×	×	×	✓	✓	×	• Total weighted sum of the squared resource usage	×
Li and Dong (2018)	×	✓	×	✓	✓	×	• Total weighted sum of the squared resource usage	×
Hosseinian et al. (2019)	×	×	×	✓	✓	×	• Makespan • Total cost	✓
Garc´ıa-Nieves et al. (2019)	×	×	×	✓	✓	×	• Makespan	×
Tirkolaee et al. (2019)	×	✓	×	✓	✓	✓	• Makespan • Net present value	×
Leyman et al. (2019)	×	✓	×	✓	×	✓	• Net present value	✓
Gn¨agi et al. (2019)	×	✓	×	✓	✓	✓	• Makespan	×
Nemati-Lafmejani et al. (2019)	×	✓	×	✓	✓	✓	• Makespan • Total cost	×
Nemati-Lafmejani and Davari-Ardakani (2020)	×	✓	×	✓	✓	✓	• Makespan • Total cost	×
Chakrabortty et al. (2020)	×	✓	×	✓	✓	✓	• Makespan	×
Turkgenci et al. (2021)	✓	✓	×	✓	✓	×	• Total cost	×
Heidari-Fathian and Davari-Ardakani (2020)	✓	×	✓	×	✓	×	• NPV of the projects • Resource usage variation	×

Table 1. Continued

Authors (year)	Multiple Projects	Multiple modes	Types of decisions		Resource-		Types of objective function(s)	Time-varying resource usage
			Selection	Scheduling	Renewable resource	Nonrenewable resource		
RezaHosseini et al. (2020)	✓	×	✓	✓	✓	×	• Total profit • Sustainable utility value • Total interruption	✓
Moomivand et al. (2020)	✓	✓	✓	✓	✓	✓	• Total profit	×
Kazemi and Davari-Ardakani (2020)	×	×	×	✓	✓	✓	• Makespan • Total cost	×
This paper	✓	✓	✓	✓	✓	✓	• Total completion times of projects • NPV of selected projects • Resource usage variation	✓

As shown in table 1, different from the related literature, this paper presents a multi-objective mixed-integer programming model to deal with multi-mode resource constrained project selection and scheduling problem considering time-varying resource consumption. In addition, both renewable and nonrenewable resources as well as generalized precedence relations between activities are considered. The aim of the proposed model is to minimize the maximum makespan of projects, minimize the variations of resource consumption between consecutive time periods, and maximize the net present value of selected projects. To the best of authors' knowledge, none of previous studies in the literature addresses all the above-mentioned issues, simultaneously.

3. Problem description and mathematical formulation

As mentioned above, this paper copes with multi-mode resource constrained project selection and scheduling problem considering both renewable and nonrenewable resources, generalized precedence relations. The main assumptions are as follows:

- A number of projects are available, of which some should be selected and scheduled.
- Activities of projects are represented in terms of precedence networks, and are subject to generalized finish-to start precedence relations with minimum time lags.
- Each activity may be performed in several modes, i.e. different time/resource combinations.
- No preemption is allowed for all activities.
- Durations of all activities are deterministic and predetermined.
- Activities of Projects need both renewable and nonrenewable resources to be completed.
- The resource usage of activities during their execution may vary with time.
- The objectives of the formulated model are minimizing the maximum completion time of activities, maximizing the net present value of executed projects and minimizing the variation of renewable resource consumption between consecutive time periods.

Parameters and indices

i	Index of activities ($i = 0,1, \dots, I, I+1$)
f	Index of projects ($f = 1, \dots, F$)
t	Index of time periods ($t = 1, \dots, T$)
k	Index of renewable resources ($k = 1, \dots, K$)
l	Index of nonrenewable resources ($l = 1, \dots, L$)
m	Index of execution modes ($m = 1, \dots, M$)
α	The maximum number of selected projects
Q	The maximum number of simultaneously executable projects
e	Interest rate
N	A very large number
ρ_{kt}	The amount of available renewable resource *k* at time period *t*
β_l	The initially available amount of nonrenewable resource *l*
NPV_f	Net present value of project *f*
d_{fim}	The duration of activity *i* of project *f* under mode *m*
r_{fimqk}	The amount of renewable resource k required for the q^{th} time period of activity *i* of project *f* under mode *m*
nr_{fimql}	The amount of nonrenewable resource l required for the q^{th} time period of activity i of project *f* under mode *m*
g_{fij}	The minimum time lag between activities *i* and *j* based on finish-to-start precedence relations

Decision variables

X_{fimt}	A binary variable which is 1, if activity *i* of project *f* is started at time period *t* under mode *m*, and 0, otherwise
y_f	A binary variable which is 1, if project *f* is selected, and 0, otherwise
u_{ft}	A binary variable which is 1, if project *f* is performed at time period *t*, and 0, otherwise
j_{kt}	A nonnegative variable to linearize the resource levelling objective function

The proposed multi-objective mixed-integer mathematical formulation pertaining to the considered problem is as follows:

$$F_1 = min\big(max\big(\Sigma_m \Sigma_t X_{f,i+1,mt}\, t\big)\big) \quad (1)$$

$$F_2 = max(\Sigma_f \Sigma_m \Sigma_t X_{f0mt}\, NPV_f \left(\frac{P}{F}, e\%, t\right)) \quad (2)$$

$$F_3 = min(\Sigma_t j_{1t}) \quad (3)$$

$$\Sigma_m \Sigma_t X_{fimt} = Y_f \qquad \forall f, i \quad (4)$$

$$\Sigma_m \Sigma_t X_{fimt}\big(d_{fim} + g_{fij} + t\big) \le \Sigma_m \Sigma_t X_{fjmt}\, t \qquad \forall f, i, j\, \epsilon\, prec(j \quad (5)$$

$$\Sigma_f \Sigma_i \Sigma_m \Sigma_{\tau=\max\{0,t-d_{fim}\}}^{t} X_{fim\tau}\, r_{fim.t-\tau.k} \le \rho_{kt} \qquad \forall k,t \qquad (6)$$

$$\Sigma_t \Sigma_f \Sigma_i \Sigma_m \Sigma_{\tau=max\{0,t-d_{fim}\}}^{t} X_{fim\tau}\, nr_{fim.t-\tau.l} \le \beta_l \qquad \forall l \qquad (7)$$

$$\Sigma_i \Sigma_m \Sigma_{\tau=max\{0,t-d_{fim}\}}^{t} X_{fim\tau}/N \le u_{ft} \qquad \forall f,t \qquad (8)$$

$$\Sigma_i \Sigma_m \Sigma_{\tau=\max\{0,t-d_{fim}\}}^{t} X_{fim\tau} \ge u_{ft} \qquad \forall f,t \qquad (9)$$

$$\Sigma_f Y_f \le \alpha \qquad (10)$$

$$\Sigma_f u_{ft} \le Q \qquad \forall t \qquad (11)$$

$$j_{1t} \ge \Sigma_f \Sigma_i \Sigma_m \Sigma_{\tau=\max\{0,t-d_{fim}\}}^{t} X_{fim\tau}\, r_{fim,t-\tau,1} - \Sigma_f \Sigma_i \Sigma_m \Sigma_{\tau=\max\{0,t-d_{fim}-1\}}^{t-1} X_{fim\tau}\, r_{fim,t-\tau-1,1} \qquad \forall t \qquad (12)$$

$$j_{1t} \ge \Sigma_f \Sigma_i \Sigma_m \Sigma_{\tau=\max\{0,t-d_{fim}-1\}}^{t-1} X_{fim\tau}\, r_{fim,t-\tau-1,1} - \Sigma_f \Sigma_i \Sigma_m \Sigma_{\tau=\max\{0,t-d_{fim}\}}^{t} X_{fim\tau}\, r_{fim,t-\tau,1} \qquad \forall t \qquad (13)$$

$$j_{kt} \ge 0\ ,\ X_{fimt}\ ,Y_f\ ,u_{ft} \in \{0,1\} \qquad (14)$$

Eqs. (1-3) represent objective functions of the proposed model, aiming to minimize the maximum makespan of projects, maximize the net present value of selected projects, and minimize the variations of resource consumption between consecutive time periods, respectively. Eq. (4) ensures that any activity can be started only in one unique time period, and can be performed under a unique execution mode, selected from a set of available modes. Eq. (5) shows the generalized finish-to-start (FS) precedence relations with minimum time lags. Eqs. (6-7) show the renewable and nonrenewable resource constraints, respectively. Eqs. (8-11) define upper bounds on the number of selected projects and the number of simultaneously executable projects in any time period. Eqs. (12-13) are used to calculate the resource usage variation in different time periods. Eq. (14) defines nonnegative and binary variables.

4. Solution techniques

A main feature of multi-objective decision-making problems is the conflicting nature of objectives, which makes attaining ideal solutions impossible. Note that an ideal solution is a solution, which is optimal in terms of all objective functions. Therefore, multi-objective optimization approaches should be used to solve the considered problem. In this section, three multi-objective optimization methods are described. These approaches are used to solve the proposed model. Then, the performance of these methods is evaluated with respect to the objective function values and CPU times.

4.1 Goal programming

The goal programming method is a widely used method for solving multi-objective decision making problems, which minimizes the (weighted) sum of deviations of objective functions from their respective goals. A simple form of goal programming formulation is as follows:

$$\min(\Sigma_{f=1}^{L} \alpha_f . h_f(d_f^+, d_f^-))$$

s.t.

$$F_f - d_f^+ + d_f^- = F_f^*$$

$$d_f^+, d_f^- \ge 0$$

Where, L and α_f represent the number of conflicting objectives, and the relative importance of different objectives, respectively. Also, F_f^* shows the goal determined for objective *f*. Moreover, d_f^- and d_f^+ show the negative and positive deviations of objective *f* from its respective goal. In addition, $h_f(d_f^+, d_f^-)$ is calculated as follows:

$$h_f\left(d_f^+ . d_f^-\right) = \begin{cases} d_f^+ & \text{for minimization problems} \\ d_f^- & \text{for maximization problems} \\ d_f^+ - d_f^- & \text{otherwise} \end{cases}$$

4.2. *ε*-constraint method

The *ε*-constraint method is another widely used method for solving multi-objective decision making problems, in which one of objectives (the most important one from the decision maker's viewpoint) is considered as the single objective function. Other objectives are used as constraints by setting appropriate lower/upper bounds, whose values are provided by applying the individual optimization method. By changing the right hand side of the appended constraints and solving the resulting optimization model, a set of Pareto-optimal solution can be obtained.

4.3. Augmented *ε*-constraint (AUGMECON) method

The augmented *ε*-constraint (AUGMECON) method (Mavrotas, 2009) is an extended version of *ε*-constraint method, aiming to generate more preferred Pareto-optimal solutions. Again in this method, the most important objective function is considered as the single objective function, and other objectives are appended to the set of constraints. The general form of AUGMECON method is as follows:

$$max(f_1(x) + eps * \left(\frac{s_2}{r_2} + \frac{s_3}{r_3} + \cdots + \frac{s_p}{r_p}\right))$$

$s.t.$

$$f_2(x) - s_2 = \varepsilon_2$$

$$f_3(x) - s_3 = \varepsilon_3$$

$$\vdots$$

$$f_p(x) - s_p = \varepsilon_p$$

$$x \in S, s_i \in R^+$$

Where, r_i, *eps* and s_i represent the range of the i^{th} objective function, a small number between 0.000001 and 0.001, and a nonnegative surplus variable pertaining to the i^{th} objective function, respectively. First, by using the individual optimization method, the worst case (NIS_{fi}) and best case (PIS_{fi}) values of all objective functions are calculated. Then, the range of objective function *i* is calculated as follows:

$$r_i = PIS_{fi} - NIS_{fi}$$

For more information about AUGMECON method and details on its implementation, one can refer to Mavrotas (2009).

Figure 1 summarizes the main features of the proposed approach to deal with MRCPSP, including the mathematical model, the utilized solution methods as well as performance assessment methods. In case of the mathematical model, decisions, main constraints, objective functions and some additional considerations are mentioned in figure 1. Moreover, as shown by figure 1, three prominent multi-objective decision making techniques, namely goal programming, *ε*-constraint method as well as augmented *ε*-constraint method, are used to solve the mathematical model. Then, Tukey test is used to statistically assess the performance of the above-mentioned solution techniques, separately for each objective function. Then, VIKOR method is used to assess the performance of the above-mentioned solution techniques in terms of all objective functions in an integrated manner.

Decisions	• Project selection` • Mode selection • Project scheduling
Constraints	• Renewable resources • Nonrenewable resources • Max no. of selected projects • Max no. of simultaneously executable projects

Objectives	• Minimization of maximum makespan • Maximization of NPV • Minimization of resource usage variation
Additional Considerations	• Generalized precedence relations between activities • Time-varying resource usage • No preemption
Solution methods	• Goal programming • ε-constraint method • Augmented ε-constraint method
Performance assessment of solution methods	• Tukey test: Statistical performance assessment in terms of objectives in a separate manner • VIKOR method: Performance assessment in terms of objectives in an integrated manner

Figure 1. The main features of the proposed approach

5. Computational results

In this section, 30 different-sized test problems, provided by the Project Scheduling Problem LIBrary* and customized to the features of the problem under consideration, are solved by using different multi-objective optimization methods, and the obtained numerical results are analyzed. To apply all solution methods, GAMS software (CPLEX solver) is utilized. Table 2 shows the values of main parameters for all 30 test problems.

Table 2. The values of main parameters for all 30 test problems

Row	Test problem code	Q	α	β_1	β_2	ρ_{1t}	ρ_{2t}	T	F
1	4-30-30-30-500-600-3-2	2	3	500	600	30	30	30	4
2	5-33-40-35-600-600-4-2	2	4	600	600	40	35	33	5
3	6-30-40-30-700-800-4-2	2	4	700	800	40	30	30	6
4	6-45-60-80-2000-2000-5-3	3	5	2000	2000	60	80	45	6
5	7-30-100-100-700-1000-4-2	2	4	700	1000	100	100	30	7
6	7-40-150-150-1000-1100-5-3	3	5	1000	1100	150	150	40	7
7	8-32-100-100-700-1000-4-2	2	4	700	1000	100	100	32	8
8	8-35-50-70-600-900-4-2	2	4	600	900	50	70	35	8
9	8-40-30-50-500-800-4-2	2	4	500	800	30	50	40	8
10	9-32-100-100-700-1000-4-2	2	4	700	1000	100	100	32	9
11	9-34-50-35-500-600-4-3	3	4	500	600	50	35	34	9
12	9-45-150-150-1000-1000-5-3	3	5	1000	1000	150	150	45	9

* http://www.om-db.wi.tum.de/psplib/

Table 2. Continued

Row	Test problem code	Q	α	β_1	β_2	ρ_{1t}	ρ_{2t}	T	F
13	9-70-250-250-2000-2000-6-3	3	6	2000	2000	250	250	70	9
14	10-40-50-48-500-600-5-2	2	5	500	600	50	48	40	10
15	10-50-200-200-1500-2000-5-4	4	5	1500	2000	200	200	50	10
16	11-45-60-60-600-700-5-2	2	5	600	700	60	60	45	11
17	11-80-200-190-2000-2000-7-5	5	7	2000	2000	200	190	80	11
18	12-100-220-200-2300-2300-8-4	4	8	2300	2300	220	200	100	12
19	12-75-160-180-2000-1900-5-3	3	5	2000	1900	160	180	75	12
20	13-40-120-120-2000-2200-4-2	2	4	2000	2200	120	120	40	13
21	13-50-80-110-1500-1200-4-3	3	4	1500	1200	80	110	50	13
22	13-70-180-180-2600-2500-6-3	3	6	2600	2500	180	180	70	13
23	13-100-250-230-2000-2000-7-4	4	7	2000	2000	250	230	100	13
24	14-60-100-20-1800-1800-5-3	3	5	1800	1800	100	20	60	14
25	14-80-180-190-2000-2100-7-3	3	7	2000	2100	180	190	80	14
26	15-70-80-100-1200-1500-4-2	2	4	1200	1500	80	100	70	15
27	15-70-80-120-1700-1800-5-3	3	5	1700	1800	80	120	70	15
28	16-60-150-150-2500-2300-5-3	3	5	2500	2300	150	150	60	16
29	17-45-100-80-1500-1800-5-3	3	5	1500	1800	100	80	45	17
30	18-40-80-100-1500-1800-4-2	2	4	1500	1800	80	100	40	18

Tables 3-5 show the objective function values and CPU times obtained by solving all 30 test problems using goal programming, ε-constraint and augmented ε-constraint methods, respectively.

Table 3. Objective function values and CPU times obtained by solving all 30 test problems using goal programming method

Row	Test problem code	F_1	F_2	F_3	CPU time
1	4-30-30-30-500-600-3-2	34	321739	27	20
2	5-33-40-35-600-600-4-2	37	321739	35	36
3	6-30-40-30-700-800-4-2	34	408696	37	60
4	6-45-60-80-2000-2000-5-3	54	956522	45	1134
5	7-30-100-100-700-1000-4-2	33	406069	28	70
6	7-40-150-150-1000-1100-5-3	44	600000	32	1125
7	8-32-100-100-700-1000-4-2	35	426087	27	29
8	8-35-50-70-600-900-4-2	38	408696	20	523
9	8-40-30-50-500-800-4-2	44	278261	22	231
10	9-32-100-100-700-1000-4-2	37	530435	29	139
11	9-34-50-35-500-600-4-2	36	400000	27	1041

Table 3. Continued

Row	Test problem code	F1	F2	F3	CPU time
12	9-45-150-150-1000-1000-5-3	48	678261	28	1269
13	9-70-250-250-2000-2000-6-3	74	1330435	50	1026
14	10-40-50-48-500-600-5-2	44	400000	27	766
15	10-50-200-200-1500-2000-5-4	54	1085217	38	1328
16	11-45-60-60-600-700-5-2	49	534783	34	1078
17	11-80-200-190-2000-2000-7-5	84	1472174	60	1064
18	12-100-220-200-2300-2300-8-4	104	1750435	60	1058
19	12-75-160-180-2000-1900-5-3	79	1333043	108	42
20	13-40-120-120-2000-2200-4-2	44	1076522	29	1007
21	13-50-80-110-1500-1200-4-3	44	1072174	33	2003
22	13-70-180-180-2600-2500-6-3	74	1585217	48	1026
23	13-100-250-230-2000-2000-7-4	104	1533043	138	1024
24	14-60-100-20-1800-1800-5-3	64	1324348	42	1026
25	14-80-180-190-2000-2100-7-3	84	1533043	56	1014
26	15-70-80-100-1200-1500-4-2	74	933043	32	2038
27	15-70-80-120-1700-1800-5-3	74	1324348	40	2008
28	16-60-150-150-2500-2300-5-3	64	133343	46	1163
29	17-45-100-80-1500-1800-5-3	49	1228696	43	1393
30	18-40-80-100-1500-1800-4-2	44	1072174	35	1023

Table 4. Objective function values and CPU times obtained by solving all 30 test problems using ε-constraint method

Row	Test problem code	F1	F2	F3	CPU time
1	4-30-30-30-500-600-3-2	30	278261	49	35
2	5-33-40-35-600-600-4-2	33	252173	44	7
3	6-30-40-30-700-800-4-2	30	278261	44	13
4	6-45-60-80-2000-2000-5-3	50	800000	123	692
5	7-30-100-100-700-1000-4-2	30	278621	47	100
6	7-40-150-150-1000-1100-5-3	41	382609	73	1002
7	8-32-100-100-700-1000-4-2	32	408696	52	255
8	8-35-50-70-600-900-4-2	37	234783	54	246
9	8-40-30-50-500-800-4-2	41	258979	36	182
10	9-32-100-100-700-1000-4-2	32	304053	49	546
11	9-34-50-35-500-600-4-2	35	252174	36	53
12	9-45-150-150-1000-1000-5-3	46	660870	70	203

Table 4. Continued

Row	Test problem code	F_1	F_2	F_3	CPU time
13	9-70-250-250-2000-2000-6-3	70	1034783	126	1003
14	10-40-50-48-500-600-5-2	42	356522	36	312
15	10-50-200-200-1500-2000-5-4	51	781626	94	1003
16	11-45-60-60-600-700-5-2	45	360870	46	1002
17	11-80-200-190-2000-2000-7-5	84	1341739	148	1004
18	12-100-220-200-2300-2300-8-4	104	1206957	128	887
19	12-75-160-180-2000-1900-5-3	75	780870	93	1004
20	13-40-120-120-2000-2200-4-2	44	928696	106	1625
21	13-50-80-110-1500-1200-4-3	44	674783	73	3071
22	13-70-180-180-2600-2500-6-3	74	1371284	25	1008
23	13-100-250-230-2000-2000-7-4	10	1047827	136	1511
24	14-60-100-20-1800-1800-5-3	64	1195390	34	1008
25	14-80-180-190-2000-2100-7-3	81	1104025	131	551
26	15-70-80-100-1200-1500-4-2	66	283567	79	1008
27	15-70-80-120-1700-1800-5-3	70	787826	118	2005
28	16-60-150-150-2500-2300-5-3	59	1112174	154	2007
29	17-45-100-80-1500-1800-5-3	46	695652	123	1821
30	18-40-80-100-1500-1800-4-2	44	328696	61	1403

Table 5. Objective function values and CPU times obtained by solving all 30 test problems using augmented ε-constraint method

Row	Test problem code	F_1	F_2	F_3	CPU time
1	4-30-30-30-500-600-3-2	32	304348	56	24
2	5-33-40-35-600-600-4-2	36	302457	46	23
3	6-30-40-30-700-800-4-2	31	391304	46	57
4	6-45-60-80-2000-2000-5-3	52	920473	105	1001
5	7-30-100-100-700-1000-4-2	31	391304	38	54
6	7-40-150-150-1000-1100-5-3	41	556522	60	66
7	8-32-100-100-700-1000-4-2	32	408696	52	116
8	8-35-50-70-600-900-4-2	38	391303	46	269
9	8-40-30-50-500-800-4-2	41	252174	40	96
10	9-32-100-100-700-1000-4-2	33	513043	49	509
11	9-34-50-35-500-600-4-2	36	400000	39	40
12	9-45-150-150-1000-1000-5-3	46	678261	79	1002

Table 5. Continued

Row	Test problem code	F_1	F_2	F_3	CPU time
13	9-70-250-250-2000-2000-6-3	73	1243478	118	1003
14	10-40-50-48-500-600-5-2	43	400000	40	336
15	10-50-200-200-1500-2000-5-4	53	1010737	74	1002
16	11-45-60-60-600-700-5-2	48	508696	36	335
17	11-80-200-190-2000-2000-7-5	84	1452024	135	1069
18	12-100-220-200-2300-2300-8-4	104	1093913	127	1007
19	12-75-160-180-2000-1900-5-3	78	1072174	110	1006
20	13-40-120-120-2000-2200-4-2	40	1067826	108	2002
21	13-50-80-110-1500-1200-4-3	40	982472	97	2720
22	13-70-180-180-2600-2500-6-3	70	669565	94	1004
23	13-100-250-230-2000-2000-7-4	103	1354851	135	1353
24	14-60-100-20-1800-1800-5-3	63	1198261	92	201
25	14-80-180-190-2000-2100-7-3	83	943189	137	1005
26	15-70-80-100-1200-1500-4-2	73	915134	65	1025
27	15-70-80-120-1700-1800-5-3	73	1289565	108	1705
28	16-60-150-150-2500-2300-5-3	64	1217391	113	2015
29	17-45-100-80-1500-1800-5-3	46	1124348	111	2003
30	18-40-80-100-1500-1800-4-2	42	1013043	98	2002

Figures 2-5 show the box plots for all objective functions and CPU times obtained by applying goal programming, augmented ε-constraint and ε-constraint methods. According to figure 2, while the mean value of the first objective function, maximum makespan of projects, obtained by goal programming method is slightly larger than the corresponding values, obtained by ε-constraint and augmented ε-constraint methods, it can be claimed that all three solution methods have almost the same performance. As figures 3 and 5 demonstrate, this is almost the case for the second objective function, net present value of selected projects, and CPU times. As figure 4 demonstrates, a different behavior is observed for the third objective function, the variations of resource consumption between consecutive time periods.

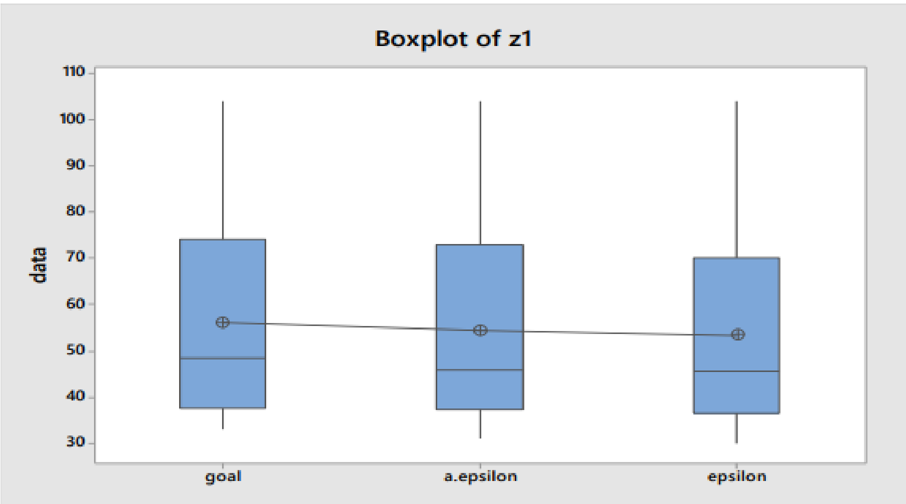


Figure 2. The box plot for the first objective function obtained by different solution methods

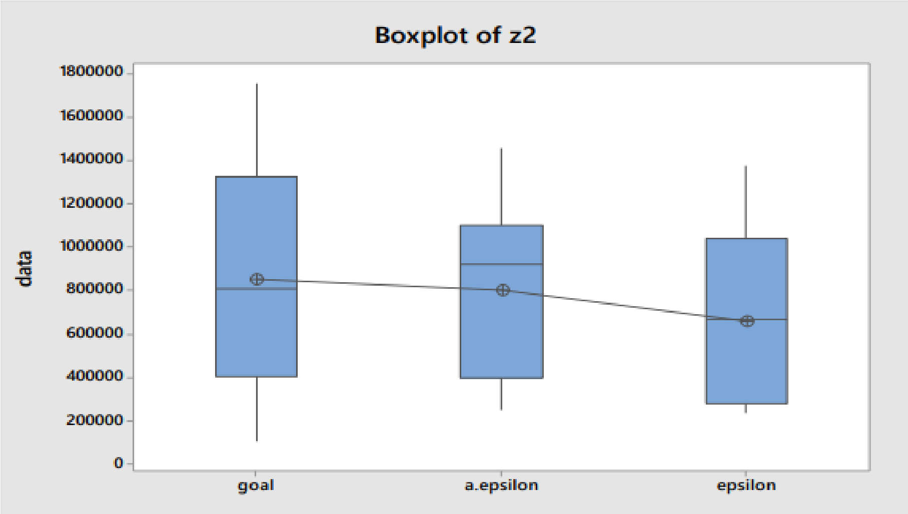


Figure 3. The box plot for the second objective function obtained by different solution methods

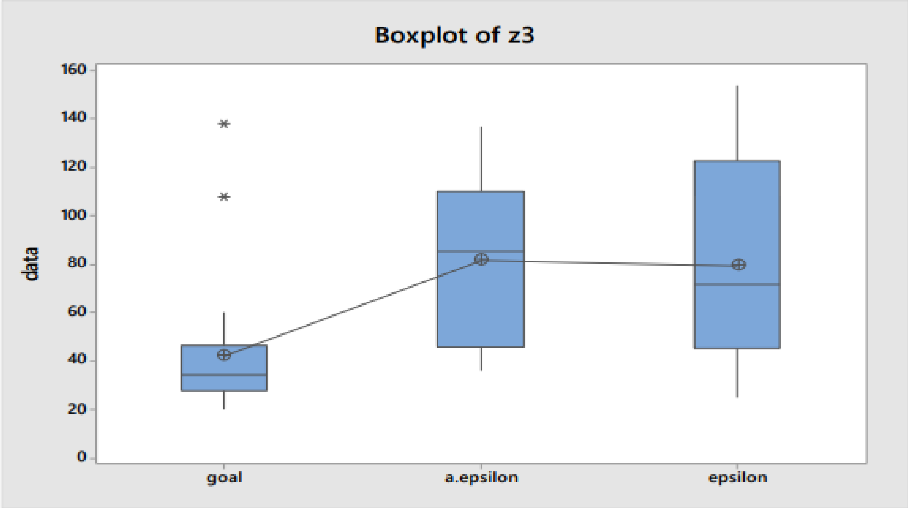


Figure 4. The box plot for the third objective function obtained by different solution methods

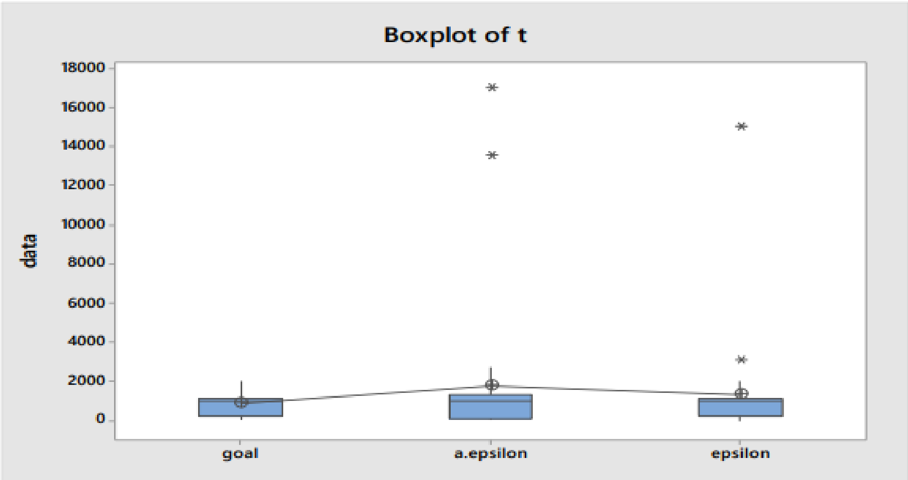


Figure 5. The box plot for the CPU time for different solution methods

For analyzing the results obtained by different solution methods from the statistical point of view, the Tukey test at the confidence level of 0.95 was used. In Tukey test, the null hypothesis states that means are equal, while the alternative hypothesis states that at least one of the means is not the same as the other means. The *p*-values obtained for the first, second and third objective function and CPU time are 0.881, 0.199, 0 and 0.442, respectively. Hence, the null hypothesis is not rejected for the first and second objective functions as well as CPU time, while, it is rejected for the third objective function. This means that the average values of the third objective function for all solution methods (goal programming,

ε-constraint and augmented ε-constraint) are significantly different at the confidence level of 0.95. In fact, Tukey test results are in accordance with those obtained by box plots (Figures 2-5).

To assess the performance of non-dominated solution methods, multi-attribute decision making (MADM) techniques can be used. In this paper, a prominent MADM technique, namely VIKOR (Opricovic and Tzeng, 2004), is utilized. The steps of VIKOR method are as follows:

- Construct the decision matrix (*F*) based on *n* alternatives and *m* attributes

$$F = [f_{ij}] \qquad i = 1, \cdots, m \ , \qquad j = 1, \cdots, n$$

- Determine the best f_i^* and the worst f_i^- values for all attributes.

$$f_i^* = \max_j f_{ij} \qquad i = 1, \cdots, m \ , \qquad j = 1, \cdots, n \qquad \text{for benefit criteria}$$

$$f_i^- = \min_j f_{ij} \qquad i = 1, \cdots, m \ , \qquad j = 1, \cdots, n \qquad \text{for cost criteria}$$

- Calculate the values S_j and R_j for all alternatives.

$$S_j = \sum_{i=1}^{m} \left(w_i \frac{f_i^* - f_{ij}}{f_i^* - f_i^-} \right)$$

$$R_j = \max_i \left(w_i \frac{f_i^* - f_{ij}}{f_i^* - f_i^-} \right)$$

where, w_i denotes the relative importance of the i^{th} attribute.

- Calculate the values Q_j for all alternatives.

$$Q_j = v \left[\frac{S_j - S^*}{S^- - S^*} \right] + (1 - v) \left[\frac{R_j - R^*}{R^- - R^*} \right]$$

$$\begin{cases} S^- = \max_j S_j \\ S^* = \min_j S_j \end{cases} \qquad \begin{cases} R^- = \max_j R_j \\ R^* = \min_j R_j \end{cases}$$

where, v is determined by the decision maker (here $v = 0.5$).

- Rank the alternatives by the values *S*, *R* and *Q* in decreasing order.

An alternative that outperforms other ones in all three groups would be the superior alternative.

Table 6 shows the decision matrix which is used as an input to compare different solution methods. Each element of this matrix has been obtained by solving all 30 test problems, and calculating average values of objective functions and CPU times for each solution method.

Table 6. Average values of objective functions and CPU times for each solution method

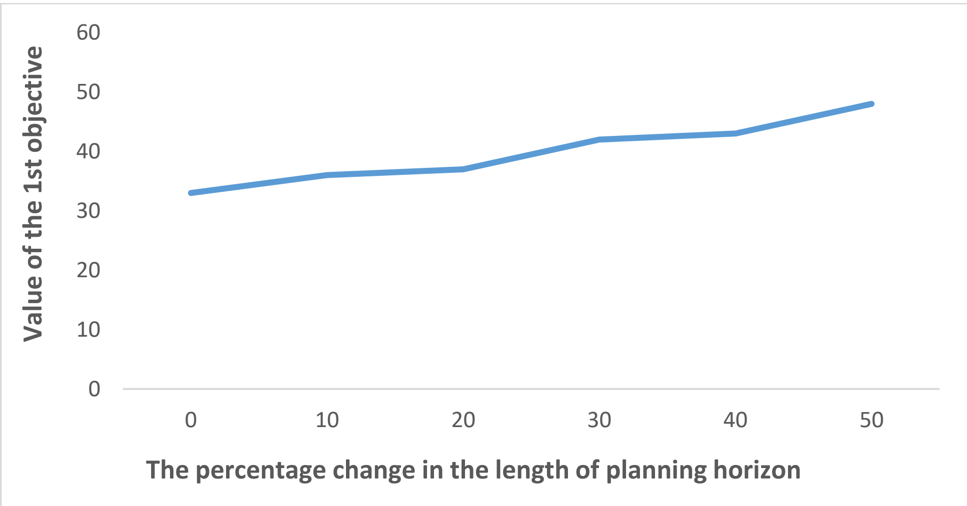
Solution method	F_1	F_2	F_3	**CPU time (seconds)**
Goal programming	56.033	849655	42.2	892.13
Augmented ε-constraint method	54.300	802218	81.800	1748.3
ε-constraint method	53.333	659413	79.60	1334.6

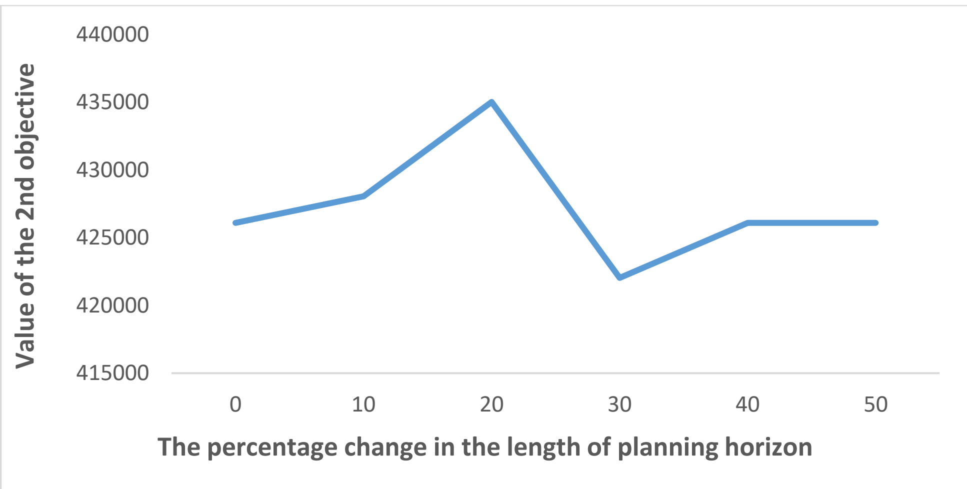
Since the weights of attributes may have a significant impact on ranking results of MADM methods, four different weight combinations have been used. The ranking results obtained by VIKOR method have been summarized in Table 7, implying that in all cases, goal programming outperforms other solution methods.

Table 7. Ranking results obtained by VIKOR method with different weight combinations

Weights				Superior solution method
F_1	F_2	F_3	CPU time (seconds)	
0.2	0.3	0.3	0.2	Goal programming
0.3	0.2	0.4	0.1	Goal programming
0.3	0.5	0.1	0.1	Goal programming
0.5	0.2	0.1	0.2	Goal programming

Following the performance assessment of different solution methods, the goal programming method was used to perform the sensitivity analysis of the main parameters of the problem under consideration. Figures 6-8 show the results of sensitivity analysis associated with changing the length of the planning horizon, the available nonrenewable resources and the available renewable resources, respectively. The important point is that the trends are not the same as those expected in the sensitivity analysis of parameters considering any of three objective functions, individually. This is due to the conflicting behavior of objective functions as well as the impact of objective weights in the goal programming method. However, as figures 6 shows, by increasing the length of the planning horizon, at least one objective function improves. As figures 7-8 show, this is also the case for the available nonrenewable resources and the available renewable resources, respectively.





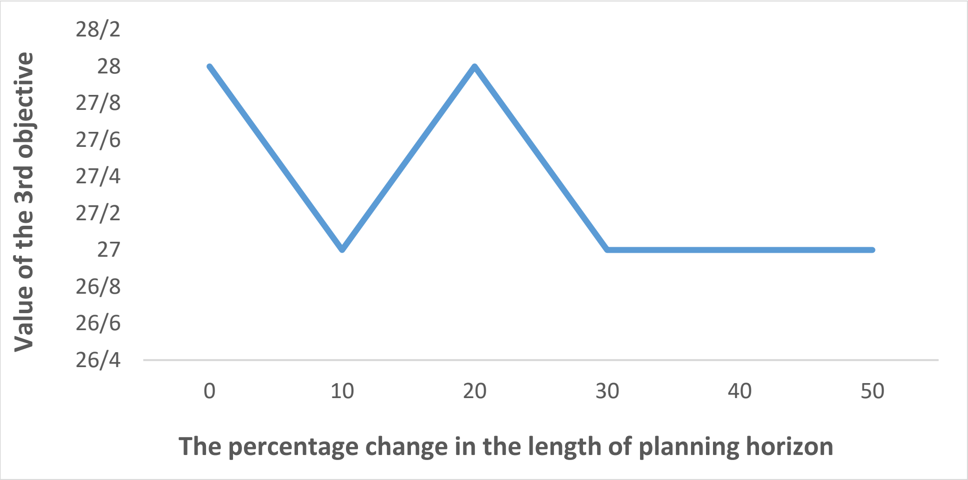
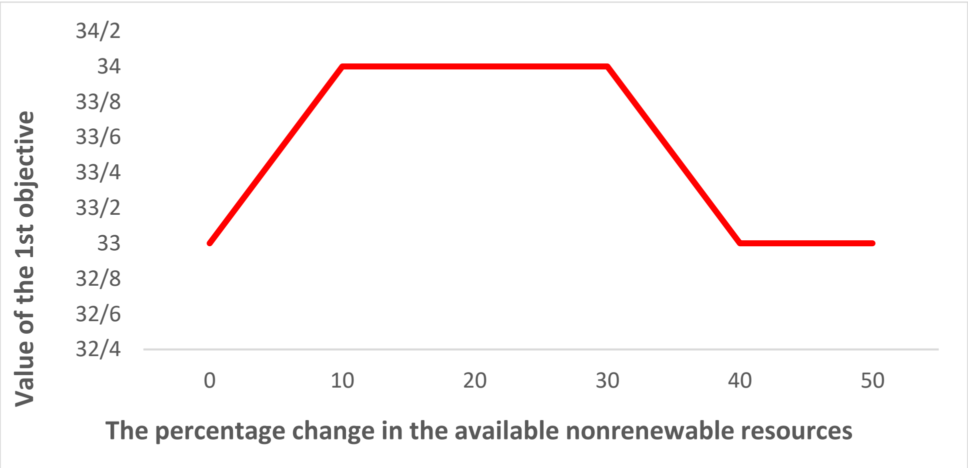
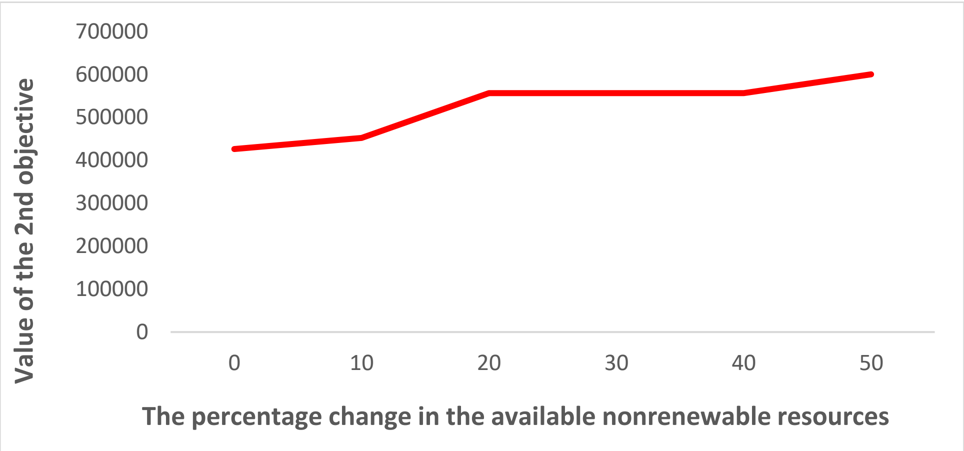


Figure 6. The results of sensitivity analysis for the length of the planning horizon





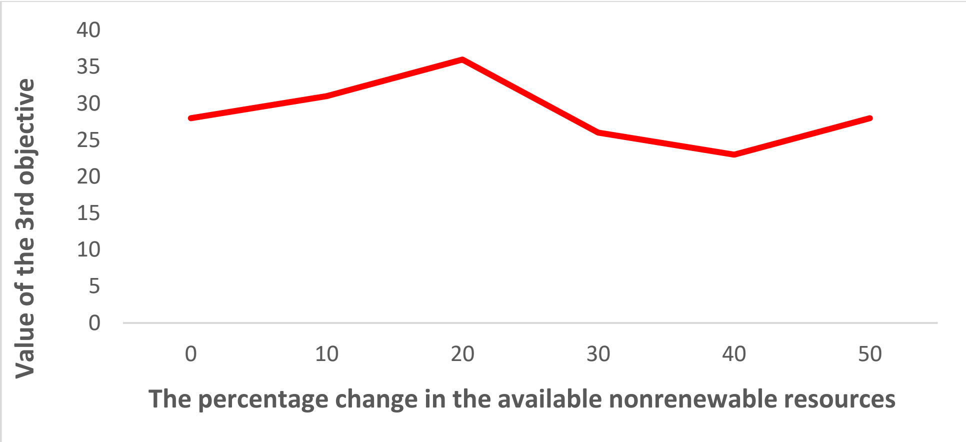
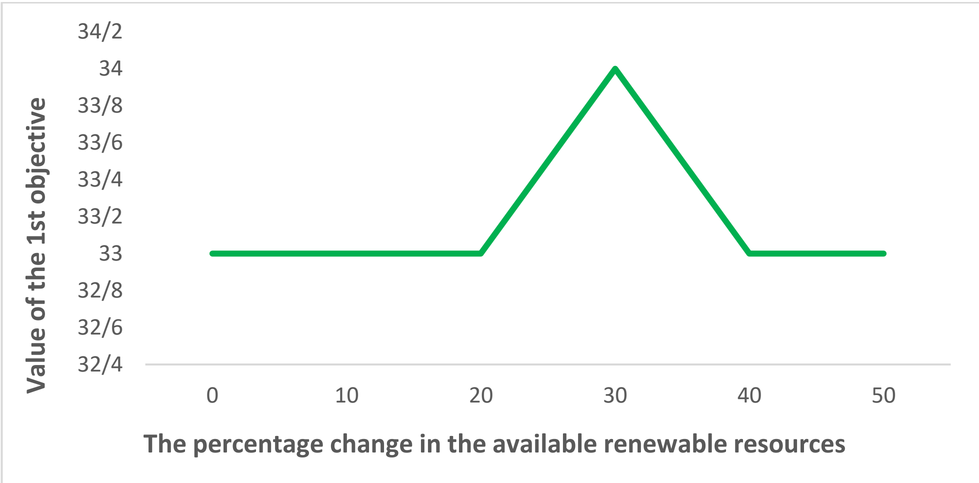
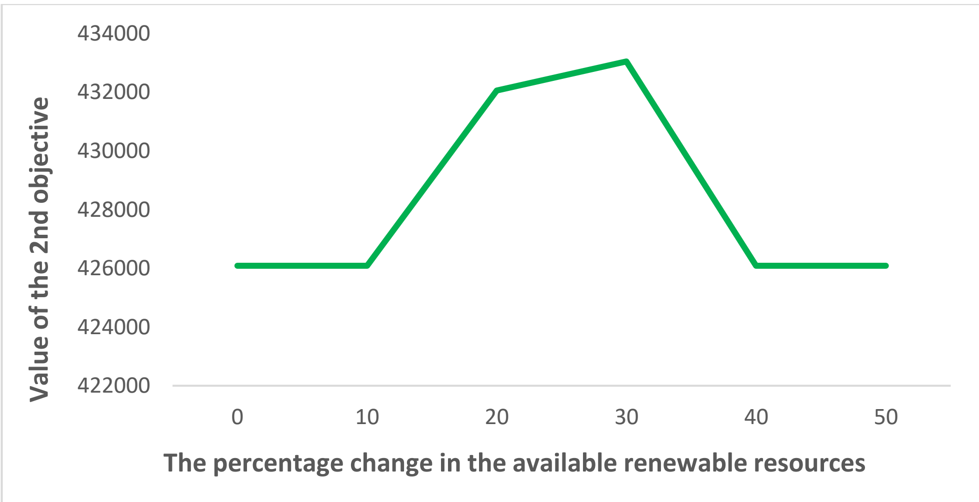


Figure 7. The results of sensitivity analysis for available nonrenewable resources





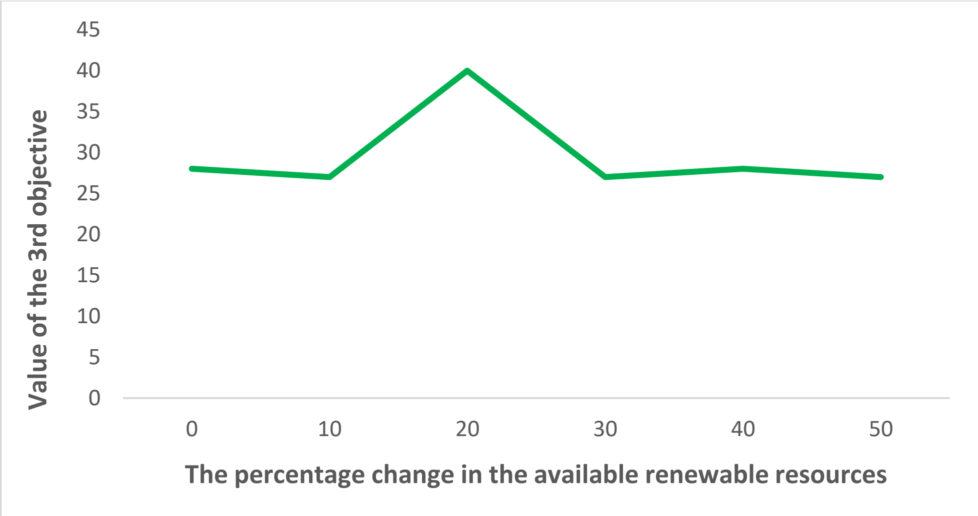


Figure 8. The results of sensitivity analysis for available renewable resources

6. Concluding remarks

This paper presented a multi-objective mixed integer programming model to cope with multi-mode resource constrained project selection and scheduling problem considering time-varying resource usage of activities and generalized precedence relations. The presented model minimizes the maximum makespan of projects, maximizes the net present values of selected projects, and minimizes the resource usage variation between consecutive time periods. Goal programming, ε-constraint and augmented ε-constraint methods were used to solve 30 different-sized test problems. Schematic and statistical analyses showed that there is no significant difference between the average values of the first and second objective functions and CPU times for all solution methods. On the contrary, goal programming outperforms other solution methods in terms of the third objective function. In addition to the above-mentioned analyses, VIKOR, as a prominent MADM method, was used to assess the performance of all solution methods. Results of applying VIKOR method confirm the superiority of goal programming method compared to ε-constraint and augmented ε-constraint methods, which are in accordance with the former schematic and statistical analyses. Furthermore, goal programming method was used to perform some sensitivity analyses by changing the length of the planning horizon, the available nonrenewable resources and the available renewable resources. Results showed that by increasing any of the above-mentioned parameters, at least one objective function improves. This is not surprising, because the objective functions of the proposed model are conflicting. It is worth mentioning that the weights of objective functions and their conflicting nature may have a significant impact on the obtained results.

As mentioned above, this main contribution of this study is that it considers some important features of project scheduling that have not been addressed by previous studies in an integrated manner. These important features are integrating project selection and project scheduling problems, considering time-varying resource usage and generalized precedence relations. These features which apply to real-world projects, make the problem a matter of particular attraction for researchers and practitioners, and confirm the practical implication of the problem under consideration.

Although authors used the data related to a prominent benchmark in the world, they did not have any access to a case study complying with all the features of the problem under consideration. This was the main limitation of this study. The availability of multi-skill resources, uncertain durations of activities, other objective functions like quality- and other resource-based objectives, and interdependence of projects are important issues that can be regarded as appropriate future research directions.

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