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Integrated bi-objective project selection and scheduling using Bayesian networks: A risk-based approach

A. Namazian*, S. Haji Yakhchali, and M. Rabbani

Department of Industrial Engineering, College of Engineering, University of Tehran, Tehran, P.O. Box 14155-6619, Iran.

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Abstract. This paper presents a novel formulation for the integrated bi-objective problem of project selection and scheduling. The first objective was to minimize the aggregated risk by evaluating the expected value of schedule delay and the second objective was to maximize the achieved benefit. To evaluate the expected aggregated impacts of risks, an objective function based on the Bayesian Networks was proposed. In the extant mathematical models of the joint problem of project selection and scheduling, projects are selected and scheduled without considering the risk network of the projects indicating the individual and interaction effects of risks impressing the duration of the activities. To solve the model, two solution approaches were developed, one exact and one metaheuristic approach. Goal Programming (GP) method was adopted to optimally select and schedule projects. Since the problem was NP-hard (Non-deterministic Polynomial-time), an algorithm combining GP method and Genetic Algorithm (GA) was proposed, hence named GPGA. Finally, the efficiency of the proposed algorithm was assessed not only based on small-size instances, but also by generating and testing representative datasets of larger instances. The results of the computational experiments indicated that it had acceptable performance in handling large-size and more realistic problems.

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1. Introduction

The permanence of organizations depends on their ability to select and implement right projects for adjusting to the competitive business environment. Thus, managers are faced with the problem of project portfolio selection and scheduling. Project portfolio selection, as a complicated decision-making process, is the procedure of evaluating individual projects and choosing a subset of them to implement so that

objectives of the organization will be satisfied. The complexity of the project selection problem is due to the high number of scenarios from which a subset (portfolio) of projects has to be chosen. After selecting a portfolio of projects, each enterprise requires to schedule them. Project scheduling consists in finding feasible start times for the activities of the projects such that the predefined objectives are optimized without violating existing precedence or resource constraints. In the recent decades, project selection and scheduling problem has received significant attention and various methods have been developed for solving it.

Models of project portfolio selection problem can be categorized in two main groups including Multi-Criteria Decision Making (MCDM) approaches for ranking the projects and mathematical programming models. Tuli et al. [1] introduced a decision-making

*. Corresponding author.

E-mail addresses: a.namazian@ut.ac.ir (A. Namazian);
yakhchali@ut.ac.ir (S. Haji Yakhchali); mrabani@ut.ac.ir (M. Rabbani)

model of multi-criteria optimization for the project selection problem. For this purpose, they combined the soft set theory and analytic hierarchical model under fuzziness. The proposed decision support strategy was useful for the project managers to take decision in the perspective environment. Rathi et al. [2] developed a project selection approach based on a combination of fuzzy and Multi Attribute Decision Making (MADM) techniques in order to determine proper Six Sigma projects in automotive companies. The weights of evaluation criteria were obtained using the Modified Digital Logic (MDL) method and final ranking was calculated by the primacy index obtained using fuzzy based VIKOR and Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) methodologies. Besides the MCDM approaches, mathematical programming is widely used for the project selection problem. The selection is a function of maximization or minimization of the objectives and satisfaction of the resource constraints. Linear Optimization (LO), Integer Linear Programming (ILP), Goal Programming (GP), and Integer Goal Programming (IGP) are more applicable mathematical optimization methods to project selection [3]. Some studies have used these methods for the project selection problem. Namazian and Haji Yakhchali [4] developed a project portfolio selection problem based on the schedule of the projects so that the minimum expected profit would be met in the shortest possible time period. In their research, because of their uncertain nature, durations of the activities were considered as semi-trapezoidal fuzzy numbers. Ultimately, they formulated the mentioned problem as a fuzzy linear programming model. Badri et al. [5] proposed a GP model for project portfolio selection in the information system projects. Arratia et al. [6] proposed a mathematical model framework for R&D project portfolio selection in which each project proposal comprised tasks with a specific type of expense. Their Mixed Integer Linear Programming (MILP) model framework handled dependencies within tasks as well as the effects of such dependencies.

Also, some scholars have used the combination of the mentioned approaches to dealing with the project selection problem. Tavana et al. [7] proposed a three-stage hybrid method for selecting an optimal combination of projects. The proposed model comprised three stages and each stage was composed of several procedures. They used Data Envelopment Analysis (DEA) for the initial screening, TOPSIS for ranking the projects, and linear Integer Programming (IP) for selecting the most suitable project portfolio. Fatemeh and Sameh Monir [8] proposed a new model for project selection using the joint approach of Analytic Hierarchy Process (AHP) and Linear Programming (LP). AHP was used first to perform the pair-wise comparisons among the selection criteria and later, to compare the

available projects against these criteria. The overall weight for each project was calculated and used as a coefficient in the LP model.

In addition to project selection, the problem of project scheduling has attracted the attention of many researchers. Kellenbrink and Helber [9] analyzed the problem of project scheduling with a flexible structure in which the activities were not completely known in advance. They presented a Genetic Algorithm (GA) to solve this type of scheduling problem and evaluated it in an extensive numerical study. Ji and Yao [10] studied a type of project scheduling problem in which durations and resource allocation times of the activities were considered as uncertain variables. They designed an uncertain programming model with the aim of minimizing the total cost and the overtime of the project under the constraints of time windows for allocating loans and the mid-term inspection. In their research, GA was employed to solve the proposed uncertain project scheduling model.

Also, the joint problem of project selection and scheduling has recently been addressed to simultaneously select and schedule projects. Tofghian and Naderi [11] developed a mixed integer linear mathematical model for the integrated multi-objective problem of project selection and scheduling. The objectives were to optimize both total expected benefit and resource usage variation. The problem of project selection and scheduling is of the NP-hard type [12]. Therefore, in recent years, meta-heuristic algorithms such as GA and colony algorithms have been proposed to solve them [13-20].

On the other hand, various methods have been developed for assessing risk in projects. For example, MCDM [21-27], Failure Mode and Effects Analysis (FMEA) [28-30], Fault Tree Analysis (FTA) [31-34], Monte Carlo Simulation (MCS) [35,36], and Bayesian Networks [37-40] are widely used to assess the risk of projects.

In the literature, the problems of project selection and scheduling, and project risk assessment have been separately investigated, and projects have been selected and scheduled without considering their risk networks. Risk network indicates the individual and interaction effects of risks within and among the projects. In practical cases, projects may affect each other negatively due to extant interactions among their risks. Since these interactions affect the duration and cost of the activities, they have a decisive role in project selection and scheduling problem. The failure to consider the effects of risks is one of the most important factors that leads to partial completion of the projects. As an example, the occurrence of a risk in one project may intensify the probability or impact of another risk in another project. To the best of our knowledge, these practical cases have not been considered in the project

selection and scheduling problem. In this context, Bayesian networks method can be used to model these interactions. In this paper, a new formulation for the integrated bi-objective problem of project selection and scheduling is proposed in which the undesirable effects of the risks of projects and their interactions are modeled by the application of Bayesian networks approach.

The problem can be described as follows. Suppose a set of projects are available in which each project has a certain duration. In each time period, each project extricates a certain benefit after its completion time. There is also a risk network stating the potential risks and interactions among them in projects. The objective is to select a subset of projects by which the aggregated risk is minimized and the total benefit is maximized. These two objectives are in conflict with each other. On the one hand, regardless of the budget or resource constraint, maximizing the earned benefit is intended by taking as many projects as available. On the other hand, selecting more projects leads to higher risk, which can reduce the benefit. To solve the problem, two exact and metaheuristic approaches are presented. First, GP method as one of the multi-objective approaches is used to achieve optimal solution. Then, due to NP-hard structure of the problem, an algorithm combining GP and GA (GPGA) is proposed to cope with more realistic large-size problems. The rest of the paper is organized as follows. In Section 2, the Bayesian belief network approach is introduced. In Section 3, the formulation developed for the problem of project selection and scheduling is presented. Section 4 presents the proposed GPGA solution method for solving the model. In Section 5, as an illustration, the developed model is applied to a small-size instance. In Section 6, the efficiency of the developed approach is assessed by generating large-size instances and finally, the paper is concluded in Section 7.

2. Bayesian networks

Bayesian networks, also called causal networks or Bayesian belief networks, are graphical representations of knowledge for reasoning under uncertainty and provide a good tool for decision analysis, including prior analysis, posterior analysis, and pre-posterior analysis [41]. Bayesian network is a general modelling approach, offering a compact presentation of the interactions in a stochastic system by visualizing system variables and their dependencies [42]. The Bayesian formula is the basis of the Bayesian network method. It reflects the interrelation between the prior probability and posterior probability and can use existing prior probability to derive the specific probability of an accident. This approach is widely used in uncertainty

analysis [43]. For n mutually exclusive hypotheses ($j = 1, 2, \dots, n$), Bayes' theorem is represented by the following relationship:

$$P(H_j|E) = \frac{P(E|H_j) \times P(H_j)}{\sum_{i=1}^n P(E|H_i) \times P(H_i)},$$

where $P(H_j|E)$ is the posterior or conditional probability for the hypothesis H ($j = 1, 2, \dots, n$) based on the obtained evidence (E), $P(H_j)$ denotes the prior probability, $P(E|H_j)$ represents conditional probability assuming that H_j is true, and the denominator represents the total probability, which is a constant value [44]. A Bayesian network consists of two main parts: a qualitative part and a quantitative part. The qualitative part is a Directed Acyclic Graph (DAG) in which the nodes reflect the system variables and the edges of the graph represent the conditional dependencies between variables. The quantitative part is a set of conditional probability functions, stating the relations between the nodes of the graph [42]. The nodes that are the starting ones and do not have an inward arrow are called the parent nodes. The other nodes, which have inward arrows connected to them, are the child nodes. In order to run the calculations, it is necessary to define the states and probabilities for each node [45]. Considering the conditional dependencies of variables, Bayesian network represents the joint probability distribution, $P(U)$, of variables $U = \{A_1, \dots, A_n\}$, as:

$$P(U) = \prod_{i=1}^n P(A_i|Pa(A_i)),$$

where $Pa(A_i)$ is the parent set of variables A_i . Accordingly, the probability of A_i is calculated as:

$$P(A_i) = \sum_{U \setminus A_i} P(U),$$

where the summation is taken over all the variables except for A_i .

Figure 1 is an illustration of a simple Bayesian network. This network consists of 5 binary variables in

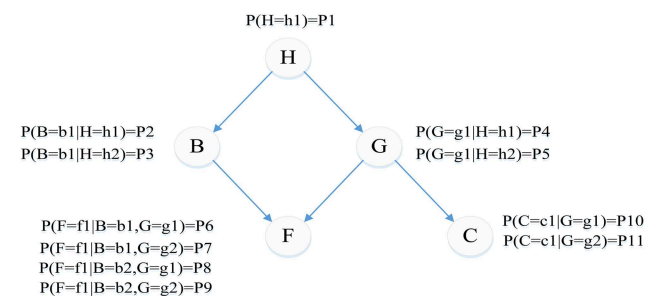


Figure 1. Bayesian network example.

which the arrows (directed links) going from one variable to another reflect the relations between variables. In this example, the arrow from B to F means that B has a direct influence on F and thus, the value of F depends on the value of B. Prior probability and conditional probabilities of variables are shown in Figure 1.

Based on Figure 1, Bayesian networks provide an appropriate structure for modeling dependencies among risks of the projects.

3. Mathematical model formulation

Most researches on project selection problem with the aim of minimizing risk have used MCDM approaches to modeling problems in which decision-making is carried out based only on risk probability and the consequences of risks are not taken into account. Furthermore, the interactions among risks, which can cause even greater consequences, have not been considered in the developed models. As mentioned before, the available mathematical models suffer from serious shortcomings including the failure to consider risks and their interactions in the project selection and scheduling problem. This section presents a new formulation for the project portfolio selection and scheduling problem with the objectives of minimizing the expected value of aggregated risk and maximizing the benefits of the projects. The developed model is based on the Bayesian networks, in which consequences and interactions of risks are simultaneously considered.

Suppose we have N projects for which each project j has n_j activities and nr_j risks. To perform the activity r of project j , its initially estimated duration is d_{rj}^0 in which the effects of extant risks are not considered. By applying the respective effects of risks, its actual duration will be d_{rj} . The notation used to formulate the model is as follows:

Indices

j, l	Project index
r	Activity index
k	Risk index
t	Time index

Parameters and decision variables

R_{por}	Project portfolio risk
R_{kj}	The risk k of project j
P_{Por}	Bayesian-based probability function of risks of the project portfolio
$R_{rlkj}^{T'}$	Initial time impact of risk k of project j on activity r of project l
R_{rlkj}^T	Cumulative time impact of risk k of project j on activity r of project l

$Pa^I(R_{kj})$	The set of internal parent risks of risk k of project j
$Pa^{E_l}(R_{kj})$	The set of external parent risks of risk k of project j from project l
$val(Pa^I(R_{kj}))$	Takes the value of 1 in the event of $Pa^I(R_{kj})$ and zero otherwise
$val(Pa^{E_l}(R_{kj}))$	Takes the value of 1 in the event of $Pa^{E_l}(R_{kj})$ and zero otherwise
$\propto_{Pa^I}^T(R_{kj})$	Percentage of increase in time impact of risk k of project j in the event of $Pa^I(R_{kj})$
$\propto_{Pa^{E_l}}^T(R_{kj})$	Percentage of increase in time impact of risk k of project j in the event of $Pa^{E_l}(R_{kj})$
N_{kj}	The number of external projects the risks of which affect risk k of project j
U_{kj}	The set of external projects the risks of which affect risk k of project j
G_{rl}	The set of risks that affect the activity r of project l
d_{rj}^0	The estimated duration of activity r of project j
d_{rj}	The actual duration of activity r of project j
j_n	The last activity of project j
es_{rj}	The earliest start time of activity r of project j
ls_{rj}	The latest start time of activity r of project j
T	Horizontal time period for implementing all projects (with index t)
T'	The time period after project completion time that is profitable (with index t')
$Pre(r, r', j)$	The predecessor relation between activities r and r' of project j
a	Interest rate
$b_{t'j}$	The benefit derived from project j in the period of time t' after project completion
y_j	Takes the value of 1 if project j is selected and zero otherwise
x_{rjt}	Takes the value of 1 if activity r of project j at time t is performed and zero otherwise

To calculate the expected value of aggregated time risk resulting from the interactions among risks, its probability and impacts should be evaluated. The respective probability part of the expected value is

evaluated by the application of Bayesian networks in which the joint probability of risks is determined by considering the states of risks and their parent risks. Thus, the first objective function is to minimize the expected value of project portfolio risk as shown in Eq. (1):

$$\begin{aligned} \text{Min } Z_1 &= E(R_{Por}^T) \\ &= \sum_{R_{kj}} \left(\prod_{k,j} P_{Por} \times \sum_r \sum_l \sum_k \sum_j R_{rlkj}^T \right), \quad (1) \end{aligned}$$

where P_{Por} is calculated as follows:

$$\begin{aligned} P_{Por} &= P(R_{kj} | Pa^I(R_{kj})) y_j \prod_{v \in U_{kj}} (1 - y_v) \\ &+ \sum_{l \in U_{kj}} P(R_{kj} | Pa^I(R_{kj}), Pa^{E_l}(R_{kj})) y_j y_l \\ &\prod_{v \in U_{kj} \setminus l} (1 - y_v) + \sum_{l1, l2 \in U_{kj}} P(R_{kj} | Pa^I(R_{kj}), \\ &Pa^{E_{l1}}(R_{kj}), Pa^{E_{l2}}(R_{kj})) y_j y_{l1} y_{l2} \\ &\prod_{v \in U_{kj} \setminus l1, l2} (1 - y_v) + \dots \\ &+ \sum_{l1, \dots, lk \in U_{kj}} P(R_{kj} | Pa^I(R_{kj}), Pa^{E_{l1}}(R_{kj}), \dots, \\ &Pa^{E_{lk}}(R_{kj})) y_j \prod_{v1 \in l1, \dots, lk} y_{v1} \\ &\prod_{v2 \in U_{kj} \setminus l1, \dots, lk} (1 - y_{v2}) + \dots \\ &+ \sum_{l1, \dots, lN_{kj} \in U_{kj}} P(R_{kj} | Pa^I(R_{kj}), Pa^{E_{l1}}(R_{kj}), \dots, \\ &Pa^{E_{lN_{kj}}}(R_{kj})) y_j \prod_{v1 \in l1, \dots, lN_{kj}} y_{v1} + (1 - y_j), \quad (2) \end{aligned}$$

where R_{rlkj}^T is calculated based on Eq. (3):

$$\begin{aligned} R_{rlkj}^T &= val(R_{kj}) y_j R_{rlkj}^{T'} \\ &\left(1 + \sum_{Pa(R_{kj})} \left[val(Pa^I(R_{kj})) \alpha_{Pa^I(R_{kj})}^T \right. \right. \\ &\left. \left. + val(Pa^{E_l}(R_{kj})) \alpha_{Pa^{E_l}(R_{kj})}^T y_l \right] \right). \quad (3) \end{aligned}$$

According to Eq. (3), the respective time impacts are determined by regarding the initial and cumulative impacts of risks on the durations of the activities. The cumulative impacts of risks represent the total impact for each risk including the initial impact and intensifying impact caused by their parent risks.

The second objective function of the model is to maximize the benefit of the selected projects as shown in Eq. (4):

$$\text{Max } Z_2 = \sum_j \sum_t \sum_{t'} \sum_{j_n} x_{rjt} \frac{b_{t'j}}{(1+a)^{t+d_{rj}+t'-1}}. \quad (4)$$

Also, the constraints of the model are shown in Eqs. (5) to (10):

$$d_{rj} = d_{rj}^0 \left(1 + P_{Por} \sum_{R_{kj} \in G_{rl}} R_{rlkj}^T \right) \quad \forall r, \forall j, \quad (5)$$

$$\sum_{t=es_{rj}}^{ls_{rj}} x_{rjt} = y_j \quad \forall r, \forall j, \quad (6)$$

$$\sum_{t=1}^{es_{rj}-1} x_{rjt} = 0 \quad \forall r, \forall j, \quad (7)$$

$$\sum_{t=ls_{rj}+1}^T x_{rjt} = 0, \quad \forall r, \forall j, \quad (8)$$

$$\begin{aligned} \sum_{t=1}^T (t + d_{rj}) x_{rjt} &\leq \sum_{t=1}^T t x_{r'tj} \\ \forall (r, r', j) &\in pre(r, r', j), \quad (9) \end{aligned}$$

$$y_j, x_{rjt} = \{0, 1\}. \quad (10)$$

Constraint (5) calculates the actual duration for each activity regarding the effective risks that may increase its duration. Constraint (6) indicates that activities of a project are scheduled if and only if the respective project is selected. According to Constraints (7) and (8), each activity is performed in its acceptable time interval. Constraint (9) shows the predecessor relationships between activities. Finally, the sign constraint corresponding to the decision variables of the model is mentioned in Constraint (10).

As can be seen, Eq. (2) is a nonlinear function in the form of multiplication of decision variables. If all decision variables are multiplied by each other, their projects have been selected to be placed in the project portfolio and the result of multiplication will be equal to one. Otherwise, at least one project is not selected and the multiplication will be equal to zero. As a

result, the multiplication of decision variables can be substituted with one new binary variable, $y = \prod_{i=1}^n y_i$, by applying the following inequalities:

$$y \geq 1 + M \left(\sum_{i=1}^n y_i - n \right),$$

$$y \leq \frac{1}{n} \left(\sum_{i=1}^n y_i \right),$$

in which M is a positive large number. In the worst case, for the problem with n projects, this model needs $(2^n - 1)$ variables, all possible subsets of projects, and $2 \times (2^n - n - 1)$ constraints to linearize the multiplication of binary variables. As a result, achieving the optimal solutions to large-size problems is not possible in a reasonable run time. In the next section, an approach is proposed to deal with this problem.

4. The proposed GPGA approach

In the present section, the proposed solution approach is presented. This approach has two steps. In the first step, the GP method is used to transfer the bi-objective model to a single-objective structure. Then, in the second step, GA is applied to obtaining the near-optimal solution to the problem.

4.1. GP method

The GP developed to deal with multi-objective decision-making problems is a mathematical programming approach to assigning optimal values to a set of variables in problems with multiple, conflicting objectives, among which there are measures of priority. This method allows one to take into account many objectives, simultaneously, while decision-making seeks the best solution among a set of feasible solutions [46]. It attempts to minimize the deviations between the desired goals and the realized results. Furthermore, these goals should be scaled based on their measurement methods. Deviation variables can be positive or negative. A positive deviation variable (d^+) represents over-achievement of the goal, while a negative deviation variable (d^-) represents under-achievement of the goal. By utilizing these deviation variables, the general GP model can be stated as follows:

$$\text{Min } \sum_i w_i p_i (d_i^+ + d_i^-),$$

$$\text{Subject to: } \sum_j a_{ij} x_j - g_i = d_i^+ - d_i^-,$$

where w_i is the weight of goal i , p_i is the priority of goal i , a_{ij} is the technological coefficient between decision variable i and constraint j , x_j is decision variable i , d_i^+ is the positive deviation variable i , d_i^- is

the negative deviation variable i , and g_i is the desired value for goal i .

4.2. Problem formulation as a GP model

To formulate the mathematical model as a GP model, the objectives and constraints are stated in the following:

- **Risk-related objective:** The aggregated risk resulting from the selected projects is evaluated based on the risk-related objective. According to Eq. (1), the respective equation is formulated as Eq. (11):

$$\text{Risk objective function} - g_r = d_r^+ - d_r^-. \quad (11)$$

g_r is the threshold of risk acceptability of the organization. It should be noted that the variable can also be set to zero if the desired value is not known.

- **Benefit-related objective:** The benefit-related objective, which is to be maximized, represents the total benefit derived from the implemented projects. As mentioned earlier, $b_{t'j}$ is the benefit derived from implementing project j at period of time t' after project completion time. According to Eq. (4), the respective equation in GP terms is formulated as:

$$\text{Benefit objective function} - g_b = d_b^+ - d_b^-. \quad (12)$$

g_b is the maximum anticipated benefit resulting from the selected projects.

- **The objective function:** The objective function attempts to minimize the sum of the deviations associated with the constraints in the model.

$$\text{Min} = w_1 (d_r^+ + d_r^-) + w_2 (d_b^+ + d_b^-). \quad (13)$$

In addition to Constraints (11) and (12), the other constraints of the model are Constraints (5) to (10).

4.3. GA structure

GA, motivated by the natural evolution process, is a robust algorithm which can be used to solve search and optimization problems. In a simple GA, first, a suitable encoding or representation of the problem should be devised. Then, a set of possible solutions treated as the population is produced through a random process. Afterwards, a fitness value is calculated for each solution in the population and then, the solutions are ranked based on their fitness values. Each solution has a chance to be selected according to its fitness value to the problem. Better solutions have higher probabilities of being selected to reproduce offspring. The individuals, during the reproduction phase, are selected from the population and recombined to produce offspring as the next generation. On the basis of a selection mechanism, a set of chromosomes is chosen for crossover and mutation. This process is called generation. The generation is iterated until the stopping conditions are met.

4.3.1. Chromosome representation

Since two processes of project selection and scheduling have to be done simultaneously, a two-level encoding scheme is used to generate solution chromosomes; project selection in the first level and project scheduling in the second level. After generating the initial population, crossover and mutation operators are applied to chromosomes in the first level to produce offspring. Then, changed chromosomes are transferred to the second level for determining scheduling of the selected projects, to be affected again by the crossover and mutation operators.

For the first level, a binary representation is used to determine the project selection process. For this purpose, a chromosome whose number of genes is as large as the number of projects is considered. Binary values are assigned to each gene for which values 1 and 0 represent the selection and non-selection of the project, respectively.

Figure 2 shows a sample chromosome for a problem with 5 projects, illustrating selection of the projects 1, 2, and 5.

At the second level, for each project selected in the previous level, a chromosome is generated for which the number of genes is determined with regard to the number of activities in the respective project. A permutation of the activities can be considered as the initial solution chromosome. Since the precedence relationship between activities may not be satisfied by the generated chromosome, the validation process should be carried out on it. Algorithm 1 can be used to validate the initial chromosome.

According to Algorithm 1, starting from the left side, each member of the initial chromosome is transferred to the respective validated chromosome if and only if all of its predecessors have previously been assigned to the new chromosome. At each step, the gene (activity) selected to be transferred to the new chromosome is removed from the previous one and

1	1	0	0	1
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Figure 2. Sample chromosome for the first level.

```

Begin
  q ← Initial Chromosome
  P ← φ
  Pred ← Predecessor(s) of the Activities
  While q ≠ φ do
    For j = q
      If Pred {j} ∈ P
        Break
      End
    End
    P ← [P, j]
    q(q == j) = []
  End
End

```

Algorithm 1. Validation procedure for the initial chromosome.

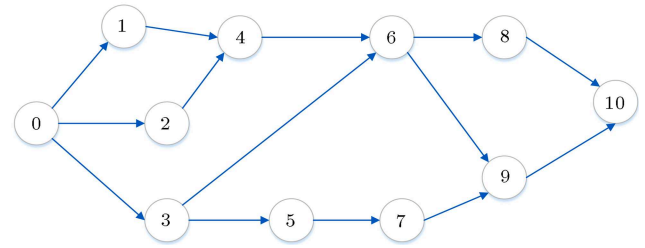


Figure 3. Sample activity network.

2	6	5	9	4	1	3	8	7
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Figure 4. The generated initial chromosome.

2	1	4	3	6	5	8	7	9
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Figure 5. The validated chromosome.

added to the new chromosome. This process continues until all members of the initial chromosome are assigned to new chromosomes. For example, assume that a project with the activity network shown in Figure 3 is selected at the first level (activities 0 and 10 are dummy).

Figure 4 illustrates an initial chromosome generated by the permutation function of its number of activities. Based on the activity network stating the precedence relationship between activities and by applying Algorithm 1, the validated chromosome will be as given in Figure 5.

4.3.2. Fitness function and selection method

As mentioned before, GP method attempts to minimize deviations of the realized results from the desired goals. Thus, the fitness function of GA is computed as:

$$\text{Fitness} = \frac{1}{w_1 (d_r^+ + d_r^-) + w_2 (d_b^+ + d_b^-)}$$

Also, to select potentially useful solutions for recombination, roulette wheel selection method is employed, in which a fitness level is assigned to the solutions. This fitness level is used to associate a probability of selection with each individual chromosome. The probability of selection is calculated for each individual as the ratio of its fitness level to the cumulative fitness of the whole population.

4.3.3. Crossover and mutation operators

In the proposed GA, due to the differences in the encoding schemes for the first level and the second level, various crossover and mutation operators are utilized to generate feasible offspring.

4.3.4. Crossover and mutation operators for the first level (project selection)

Chromosomes in the first level have binary values. Thus, in order to generate offspring, the following

Parents	1	1	0	1	0	0	0	1
	0	1	1	0	1	0	0	1
	0	1	1	0	1	1	0	0
Offspring	0	1	1	0	1	0	0	1

Figure 6. Three-parent crossover operator.

crossover operator can be used. First, three parents are randomly selected. Each gene from the first parent is compared with the same gene from the second parent. If they are the same, this gene is transferred to the offspring. If they are not the same, it is compared with one from another parent. In the case of similarity with the gene from the third parent, the gene from the first parent and otherwise, the gene from the third parent is transferred to the offspring. This three-parent crossover operator is graphically illustrated in Figure 6.

For mutation in the first level, a simple binary mutation operator can be used. One gene from the parent is randomly selected and its values are replaced by another binary value.

4.3.5. Crossover and mutation operators for the second level (project scheduling)

To produce offspring from parents, the traditional crossover and mutation operators may generate infeasible solutions in which some activities are duplicated or missing in the respective offspring. To avoid illegal offspring, the following genetic operators can be used. These operators generate feasible solutions in which activities are not duplicated or missing. After using these operators, Algorithm 1 should be applied to verifying the generated solutions regarding the precedence relationships between activities.

- **Partially Mapped Crossover (PMX).** The PMX operator acts as a two-point crossover for sequence encoding through a repairing procedure. Having selected a pair of parents, the sequences of activities between two randomly specified positions are exchanged. The resulting offspring may not be feasible due to duplication of activities. Therefore, a mapping is established for the exchanged parts. Finally, a repairing procedure that replaces the repeated activities by their corresponding activities is applied to legalizing the offspring. The procedure of the PMX operator is illustrated in Figure 7.
- **Order Crossover (OX).** The OX operator produces offspring by transferring a subsequence of random length and position from one parent, and filling the remaining positions according to the order from the other parent. A subsequence between two random positions of a parent is transferred to one of the offspring in the same position. The activities

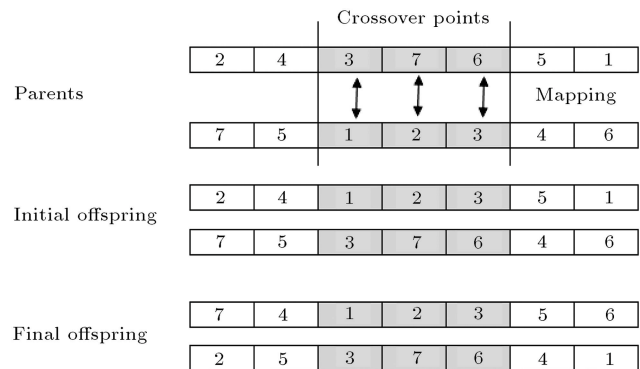


Figure 7. PMX operator.

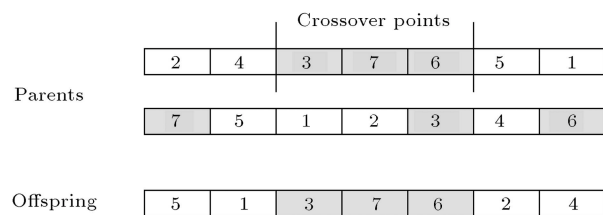


Figure 8. OX operator.

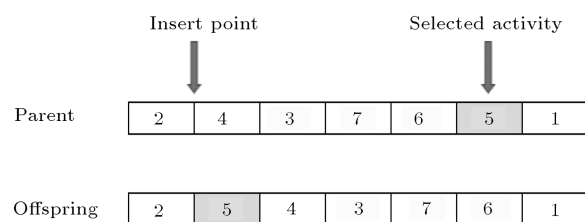


Figure 9. IM operator.

that are already in the subsequence are removed from the second parent. The unselected activities in the second parent are then inserted into the empty positions of the offspring while preserving their original orders in the parent. This operator is shown in Figure 8.

- **Insert Mutation (IM).** The IM operator randomly selects a position and inserts the activity in the position into another random point. The procedure of the IM operator is illustrated in Figure 9.
- **Swap Mutation (SM).** The SM operator randomly selects two positions and then, swaps the activities in the positions as illustrated in Figure 10.

5. Numerical example

As an illustration of the developed model, a numerical example is presented in this section.

5.1. Sample problem

In the sample problem, as shown in Figure 11, a network consisting of three projects is considered in which each project contains seven activities. The network of these projects and durations of the activities

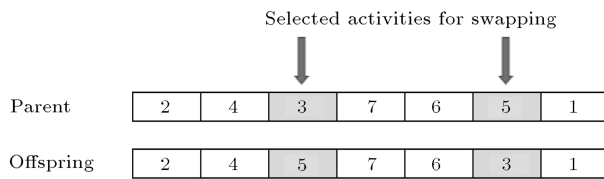


Figure 10. SM operator.

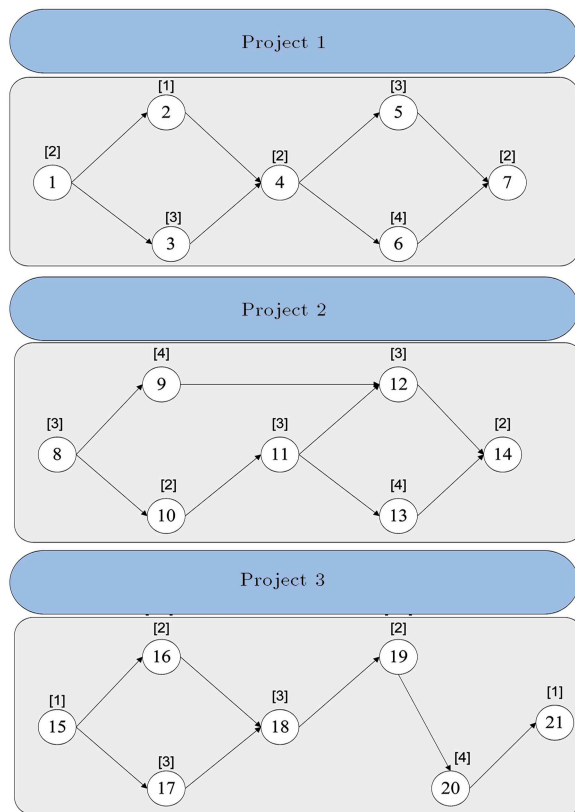


Figure 11. Network of the projects.

are shown in Figure 11. The benefits of the projects in the time periods after project completion time are stated in Table 1. In this problem, the interest rate is assumed to be 0.1.

The supposed risk network of the projects, including the risks and their interactions, is shown in Figure 12.

Figure 12 indicates that in addition to the interactions among risks in each project, some risks from one project can affect the risks in other projects. For

Table 1. Benefits of the projects.

		Time periods after project completion time (t')				
		1	2	3	4	5
Project	P1	14	16	20	24	29
	P2	13	15	20	25	31
	P3	12	17	23	27	33

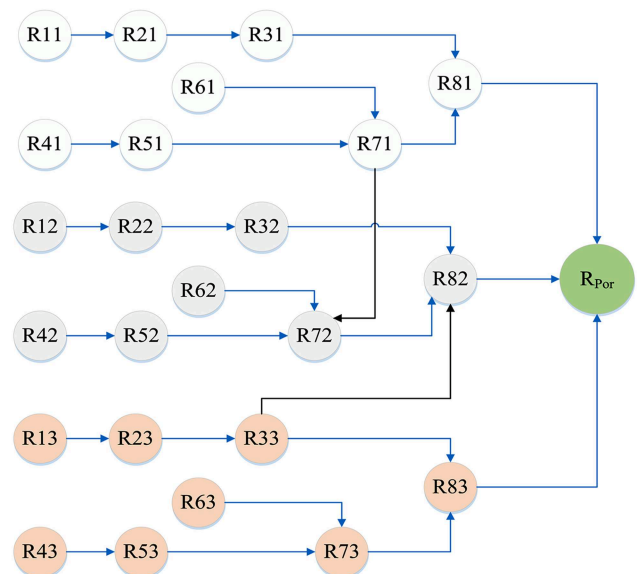


Figure 12. Network of the risks.

example, risk R71 from project 1 has an impact on risk R72 of project 2. This means that in the case of selecting both projects 1 and 2, the occurrence of the risks in project 1 can increase the probabilities or consequences of risks in project 2. Furthermore, risks in each project, if selected, affect the project portfolio risk and may increase durations of activities of the respective project as well as activities of other projects.

The predecessor relationships between activities as well as the earliest and latest times for each activity and their effective risk(s) are presented in Table 2.

5.2. Risk prior and conditional probability assessment

Prior probability can be interpreted as the evaluated probability of a risk, which is not affected by other activated risks. On the other hand, conditional probability can be interpreted as the evaluated probability of a risk, which is impressed by another risk inside the network. Qualitative scales are often used to express such probabilities with 5 to 10 levels. In this paper, we use the 5-level scale to present prior and conditional probabilities of risks as shown in Table 3.

5.3. Risk impact assessment

Impact or consequence refers to the extent to which a risk might affect the project. The main impact assessment criteria include time, cost, quality, and scope. In this paper, the time effects of risks are considered, although they can be generalized to cost factor. The assessment methods for time and cost effects of risks are shown in Table 4.

In addition to the independent effect of each risk on the project risk assessment criteria, the interactions among risks will amplify these effects. To assess the severity of the effects of risks on each other, we use the

Table 2. Predecessor relationships, start times, and finish times of the activities.

Activity	1	2	3	4	5	6	7
Predecessor(s)	-	1	1	2 3	4	4	5 6
EST	0	2	2	5	7	7	11
EFT	2	3	5	7	10	11	13
LST	0	4	2	5	8	7	11
LFT	2	5	5	7	11	11	13

Effective risk(s)	R11	R21 R31	R41	R51	R61	R71	R81
Activity	8	9	10	11	12	13	14
Predecessor(s)	-	8	8	10	9 11	11	12 13
EST	0	3	3	5	8	8	12
EFT	3	7	5	8	11	12	14
LST	0	5	3	5	9	8	12
LFT	3	9	5	8	12	12	14

Effective risk(s)	R12	R22	R32 R42	R52	R62	R72	R82
Activity	15	16	17	18	19	20	21
Predecessor(s)	-	15	15	16 17	18	19	20
EST	0	1	1	4	7	9	13
EFT	1	3	4	7	9	13	14
LST	0	2	1	4	7	9	13
LFT	1	4	4	7	9	13	14

Effective risk(s)	R13	R23 R33	R43	R53	R63	R73	R83
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Table 3. Scales of prior and conditional probabilities.

Annual frequency			Probability	
Descriptor	Definition		Descriptor	Value
Frequent	Up to once in 1 month or more		Very high	0.9
Likely	Once in 1 month up to once in 6 months		High	0.7
Possible	Once in 6 months up to once in 18 months		Medium	0.5
Unlikely	Once in 18 months up to once in 30 months		Low	0.3
Rare	Once in 30 months or less		Very low	0.1

Table 4. Time and cost impact assessment.

Value		0.05	0.1	0.2	0.4	0.8
Descriptor		Very low	Low	Moderate	High	Very high
Risk assessment criteria	Time	Insignificant time increase	< 5% time increase	5-10% time increase	10-20% time increase	> 20% time increase
	Cost	Insignificant cost increase	< 10% cost increase	10-20% cost increase	20-40% cost increase	> 40% cost increase

Table 5. Interactive time and cost impact assessment.

Value		0.05	0.1	0.15	0.2	0.25
Descriptor		Very low	Low	Moderate	High	Very high
Risk assessment criteria	Time	Insignificant time increase	< 5% time increase	5-10% time increase	10-20% time increase	> 20% time increase
	Cost	Insignificant cost increase	< 10% cost increase	10-20% cost increase	20-40% cost increase	> 40% cost increase

5-level scale, as shown in Table 5, for the assessment of impacts.

The values in the above table have been set so that the maximum change in the cumulative effects is equal to one.

5.4. Project portfolio risk assessment

Based on the identified risks and their relationships, the Bayesian networks-based model can be built using the software AgenaRisk. In a Bayesian network, for each variable (risk), the variable status as well as its table of prior and conditional probabilities should be determined. The status of each variable is determined based on its conditions during the projects. For example, the variable R_{Por} (project portfolio schedule delay risk) is assigned two states, namely ‘Low’ and ‘High.’ Thus, the remaining variables have two opposite states: ‘True’ indicates occurrence of the risk and ‘False’ indicates its non-occurrence. The assignments ‘Low’ and ‘High’ are defined as time-overrun durations, which are less than 15% and greater than 15% compared to the original schedule for completing the project portfolio, respectively. It should be noted that these computations can also be performed for cost-overrun expenditures compared to the original budgeting. However, in this study, only the time criterion is discussed.

Tables of prior and conditional probabilities for the variables ‘project portfolio schedule delay risk’ (R_{Por}) and $R71$, as an example, are shown in Figures 13 and 14, respectively.

Finally, the Bayesian networks-based model and evaluated probabilities for states of project portfolio risks are shown in Figure 15.

Figure 6 illustrates the model output for the project portfolio. It is estimated that the probability of schedule delay in the project portfolio is approximately 0.47 for the state of ‘Low,’ whereas it is 0.53 for the state of ‘High.’ As a result, the duration of the

R51	False		True	
R61	False	True	False	True
False	0.3	0.1	0.1	0.5
True	0.7	0.9	0.9	0.5

Figure 14. Conditional probability table for the output variable ‘ $R71$ ’.

project portfolio tends to get extended with time-overrun durations greater than 15% of the original duration.

The consequences associated with individual risks and parent risks are stated in Table 6.

According to Table 6, for example, the individual time consequence of $R71$ is 0.8, and risks $R51$ and $R61$ are its parent risks. As a result, in a situation that $R71$ and at least one of its parent risks have occurred, the time consequence of $R71$ will be increased.

5.5. Model results

The results of problem formulation as a GP model are shown in Table 7.

Table 7 illustrates the selected project(s) for different values of targets and weights of goals. As shown in this table, when the weight of the risk-related objective is increased, the optimal solution includes only project 2, whereas increasing the weight of the benefit-related objective leads to selecting all the projects to be placed in the project portfolio. Consequently, the higher the value of the risk-related target, the greater the number of projects in the project portfolio. In other words, in the case that the threshold of risk acceptability of the organization is increased, more projects are selected to construct the project portfolio. In the case of selecting all projects (e.g. $w1/w2 = 40$, $g1 = 1$ and $g2 = 70$), each project is scheduled as shown in Table 8.

According to Table 8, activities can be started at their earliest start times. The durations of activities

R81	False				True			
R82	False		True		False		True	
R83	False	True	False	True	False	True	False	True
Low	0.7	0.5	0.7	0.5	0.3	0.5	0.1	0.3
High	0.3	0.5	0.3	0.5	0.7	0.5	0.9	0.7

Figure 13. Conditional probability table for the output variable ‘project portfolio schedule delay’.

Table 7. Optimal solutions for different targets and weights.

$w1/w2 = 80$			$w1/w2 = 40$			$w1/w2 = 20$		
$g1$	$g2$	Selected project(s)	$g1$	$g2$	Selected project(s)	$g1$	$g2$	Selected project(s)
0.2	30	P2	0.2	30	P2	0.2	30	P2
0.2	40	P2	0.2	40	P2	0.2	40	P2
0.2	50	P1, P3	0.2	50	P2	0.2	50	P2
0.2	60	P1, P3	0.2	60	P2	0.2	60	P2
0.2	70	P1, P2, P3	0.2	70	P2	0.2	70	P2
0.4	30	P3	0.4	30	P3	0.4	30	P3
0.4	40	P3	0.4	40	P3	0.4	40	P3
0.4	50	P1, P3	0.4	50	P3	0.4	50	P3
0.4	60	P1, P3	0.4	60	P3	0.4	60	P3
0.4	70	P1, P2, P3	0.4	70	P1, P2, P3	0.4	70	P3
0.6	30	P1	0.6	30	P1	0.6	30	P1
0.6	40	P2, P3	0.6	40	P1	0.6	40	P1
0.6	50	P1, P3	0.6	50	P1, P3	0.6	50	P1
0.6	60	P1, P3	0.6	60	P1, P3	0.6	60	P1
0.6	70	P1, P2, P3	0.6	70	P1, P2, P3	0.6	70	P1
0.8	30	P1	0.8	30	P1	0.8	30	P1
0.8	40	P1, P2	0.8	40	P1, P2	0.8	40	P1, P2
0.8	50	P1, P3	0.8	50	P1, P3	0.8	50	P1, P2
0.8	60	P1, P2	0.8	60	P1, P2	0.8	60	P1, P2
0.8	70	P1, P2, P3	0.8	70	P1, P2, P3	0.8	70	P1, P2
1	30	P1	1	30	P1, P2	1	30	P1, P2
1	40	P1, P3	1	40	P1, P3	1	40	P1, P2
1	50	P1, P3	1	50	P1, P3	1	50	P1, P2
1	60	P1, P3	1	60	P1, P3	1	60	P1, P2
1	70	P1, P2, P3	1	70	P1, P2, P3	1	70	P1, P2

Table 8. Schedules of the projects.

Project	Activity	Start time	Project	Activity	Start time	Project	Activity	Start time
	1	0		8	0		15	0
	2	3		9	4		16	2
	3	3		10	4		17	2
1	4	7	2	11	8	3	18	6
	5	10		12	12		19	10
	6	10		13	12		20	13
	7	15		14	17		21	18

are increased due to the effects of risks inside and between projects. In other word, the set of selected projects has an influential role in the exact duration for implementing each activity. The time required to perform all projects is a 20-time period. Furthermore, the positive deviation variable concerning the first objective function (d_1^+) and the negative deviation variable concerning the second objective function (d_2^-) are 0.514 and 0.582, respectively, which indicate the reasonable satisfaction of the targets.

6. Test problems

In this section, several instances are generated to test the performance of the proposed GPGA in comparison with the exact solutions obtained by the GP method.

To verify the efficiency of the algorithm, ten problems in small and medium sizes are designed and the results obtained by this method are compared with the results from the exact formulation of the problem. Finally, the result of the algorithm will be reported for large-size instances, as the exact formulation is unable to solve them.

6.1. Instance generation

To generate instances, a number of 4 or 5 risks to 30 projects are investigated. For each project, 4, 5, or 6 risks are considered. For the sake of simplicity, we assume the number of activities equal to the number of risks for each project. Benefits of projects are determined by a ten-digit discrete uniform distribution with numbers between [16,25] for the first period after

Table 9. Comparison between two developed approaches.

Problem no.	Project	Activity	Risk	GP		GPGA	
				Objective	Run time (min)	Objective	Run time (min)
1	5	20	20	24.68	3	24.68	1
2	6	24	24	30.32	8	30.32	1
3	7	28	28	38.61	14	38.61	1.6
4	8	32	32	48.83	23	49.81	1.7
5	9	36	36	60.22	31	62.04	1.8
6	12	48	48	75.76	48	78.03	2.3
7	14	56	56	94.33	66	97.65	2.4
8	14	70	70	118.22	84	122.59	2.5
9	16	64	64	147.21	108	152.80	2.9
10	20	80	80	—	*	185.22	4.1
11	22	88	88	—	*	231.84	4.3
12	24	96	96	—	*	290.74	4.7
13	26	104	104	—	*	362.01	5.2
14	28	112	112	—	*	454.11	5.4
15	30	120	120	—	*	564.24	5.9

* Means the approach is not able to solve the instance in a reasonable run time.

the completion time. Benefits grow by up to 5-time periods with the rate of 10%. The ratio of two objective functions is equal to 40 and their desired goals are determined by the application of two discrete uniform distributions of [0.2, 0.4, 0.6, 0.8, 1] and [30, 40, 50, 60, 70]. Duration of each activity is randomly specified based on an eight-digit discrete uniform distribution with numbers between [3, 10]. For assigning each risk to an activity of the project, risks and activities are randomly selected so that each activity is affected by only one risk. Also, the risk network of projects stating the interactions among risks is constructed as follows. First, among all projects, two projects are randomly selected and then, one risk is specified in each project. Finally, one of them is randomly selected to affect another one. This process continues as much as the number of projects. Also, by applying this process in each project, the interaction structure of risks is determined. Respective prior or conditional probabilities as well as the main time impact for each risk are specified by the application of continuous uniform distribution, i.e., [0 1]. Also, the intensifying impact of each risk is randomly determined according to the discrete uniform distribution with numbers [0.05, 0.1, 0.15, 0.2, 0.25].

6.2. Computational results

As mentioned earlier, five small-size and five medium-size instances have been designed to assess the efficiency of the proposed GA approach compared with the exact solutions obtained by the GP method. The results for the generated instances are shown in Table 9.

Table 9 indicates that the average error between the solutions of the two methods for the first ten instances (small and medium sizes) is about 3%, which

shows that, on average, GA has generated near optimal solutions. On the other hand, the required run time of GA is significantly less than that of the exact approach. Five large-size instances are designed and solved by this approach. As marked by (*), the exact approach is not able to solve the instances with sizes greater than 16 projects in a reasonable run time, i.e., less than two hours. Regarding the closeness of the solutions of the proposed GA to those of the exact approach, it has acceptable performance and is efficient and reliable enough to handle large-size instances and more realistic problems, which are not solvable using the exact method.

7. Conclusion

Project selection is a crucial decision in almost every company, particularly in project-based organizations, and has a significant role in the performance of an organization. Risks are the main causes of indeterminacy in projects and affect the duration of activities. This paper studied a novel formulation of the joint problem of project selection and scheduling by evaluating the individual and intensifying impacts of risks on duration of the activities of the projects. In the developed mathematical model, two objectives were considered. The first objective was to minimize the aggregated risk and the second objective was to maximize the total benefit of the projects, by which each project released a certain benefit in each time period after its completion time. Regarding the risk network of the projects, stating the potential risks and their interactions, Bayesian networks-based objective function was developed to evaluate the expected impacts of risks.

Two solution approaches were applied to selecting

and scheduling projects in exact and approximate manners. The presented formulation provided a multi-objective mathematical model and the GP method was used to optimally select and schedule projects. Since the problem was NP-hard, an algorithm, which combined Goal Programming (GP) method and Genetic Algorithm (GA), named GPGA, was proposed. Then, the presented model was verified through a generated sample problem. Also, the efficiency of the proposed metaheuristic algorithm compared with the exact approach was assessed through generating small- and medium-size instances. Accuracy of the generated solutions indicated that the metaheuristic algorithm had an acceptable efficiency in dealing with large-size problems. To make the structure presented in this paper more applicable, it is suggested that this problem can be extended to resource-constraint project selection and scheduling or to a problem of selecting risk response strategies aimed at mitigating the impacts of risks.

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Biographies

Ali Namazian received his BSc and MSc degrees in Industrial Engineering from Yazd University and Sharif University of Technology, Iran, respectively. He is currently a PhD candidate in Industrial Engineering at University of Tehran, Iran. His research interests include project selection and scheduling, project management, multivariate and statistical analysis, multi-criteria decision-making, and advanced operation research.

Siamak Haji Yakhchali is an Assistant Professor of Industrial Engineering in the School of Industrial and Systems Engineering at the University of Tehran, Iran. He received his MSc and PhD degrees in Industrial

Engineering from Amirkabir University of Technology, Tehran, Iran. Also, he was a postdoctoral research fellow at the University College London. His expertise lies mainly in the field of project scheduling and project management.

Masoud Rabbani is a Professor of Industrial Engineering in the School of Industrial and Systems Engineering at the University of Tehran, Iran. He has published more than 50 papers in international journals, e.g., European Journal of Operational Research, International Journal of Production Research, and International Journal of Production Economics. His current research interests comprise production planning, applied graph theory, productivity management, and EFQM.