Computers & Industrial Engineering 61 (2011) 226–237

Contents lists available at ScienceDirect

Computers & Industrial Engineering

journal homepage: www.elsevier.com/locate/caie

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A comprehensive framework for project selection problem under uncertainty and real-world constraints ☆

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ARTICLE INFO

Article history:
Received 30 August 2010
Received in revised form 26 March 2011
Accepted 29 March 2011
Available online 2 April 2011

Keywords:
Project selection
PROMETHEE
Uncertainty
Monte Carlo simulation

ABSTRACT

This paper proposes a comprehensive framework for project selection problem under uncertainty and subject to real-world constraints, like segmentation, logical, and budget constraints. The framework consists of two main phases. In the first phase, the candidate projects are ranked considering the uncertainty, through a Monte Carlo simulation linked to a multi-criteria approach. In the second phase, the overall complete preorder of the projects in different iterations is first determined and then used in another Monte Carlo simulation linked to an integer programming module in order to effectively drive the final portfolio selection while satisfying the budget, segmentation and other logical constraints. The proposed framework is implemented in a case study to show its usefulness and applicability in practice. Finally, a comparison is carried out between the proposed approach and its deterministic counterpart and the corresponding results are discussed.

1. Introduction

A project will not be successful unless all, or at least most of the participants are not only competent but also motivated to produce a satisfactory outcome. To achieve this, a number of methods, procedures and techniques have been developed, which together with the general management and people skills, enable the project manager to meet the set criteria of time cost and performance/quality in the most effective way (Lester, 2007).

Operational Research (OR) has given essential scientific contributions to the success of Project Management not just through multiple models to understand and to represent projects but also by the development of algorithms and aids to support the decisional role of project manager. Tavares (2002) has discussed the major contributions of OR to the project management area. In this regard, a well-known problem, addressed by different OR techniques, is project selection.

Project selection is a strategic decision problem which is often characterized by multiple, conflicting and incommensurate criteria (Liesiö, Mild, & Salo, 2007) while the decision maker (DM) has to decide a portfolio of the most attractive alternatives by taking into account different aspects of the projects' efficiency (Mavrotas, Diakoulaki, & Kourentzis, 2008). In other words, in the project selection problem a decision maker allocates limited resources to a set of competing projects, considering one or more corporate goals or objectives (Medaglia, Graves, & Ringuest, 2007).

Project selection is a very complex decision making process since it is affected by many critical factors such as the market conditions, raw materials availability, probability of technical success and government regulations (Bard, Balachandra, & Kaufmann, 1988). In addition, there is a high level of risk for the uncertainty or incompleteness of project information which make the DM feel hard to analysis correctly (Wang, Xu, & Li, 2009). Obviously, wrong decisions in project selection have two negative consequences: On the one hand, resources are spent on unsuitable projects and, on the other hand, the organization loses the benefits it could have gained if these resources had been spent on more suitable projects (Martino, 1995).

In this paper, a comprehensive framework is introduced that considers real-world constraints and deals with all possible kinds of uncertainties in the input data of project selection problem, i.e., performance values (PVs), criteria weights (CWs) and preference thresholds. In the first phase, the PROMETHEE method linked to a Monte Carlo simulation structure is implemented in order to rank the candidate projects. The output of simulation provides the probabilities of achieving different ranks for each project. Then, a linear assignment model is adapted to calculate the overall rankings amongst all simulation iterations. In the second phase, overall rankings are used for another Monte Carlo simulation by which the augmented scores are determined and fed into an integer programming (IP) model. This IP model has been inspired from Mavrotas et al. (2008) in which the most proper projects are selected based on the augmented scores and subject to budget, segmentation and

☆ This manuscript was processed by area editor Willy Herroelen.

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doi:10.1016/j.cie.2011.03.015

other possible constraints. The IP model overcomes the bias against low cost combination of projects which is usually occurred in the knapsack-type formulation. Also, the IP model used here does not need the total scores reported by MCDA method but it needs only the ordinal ranks of the projects. Another benefit of this IP model is its protection against the rank reversal problem which often occurs when ranking multiple projects using MCDA techniques with different input parameters.

The main contributions of the paper are twofold: Lowering the uncertainty level of important input data and identifying those resources that their capacities should be extended. That is, we first try to find those uncertainties that have the most impact on the ranking of the projects. In this way, the decision makers will be able to concentrate on the most important areas and make lower their uncertainties via increasing their knowledge. Furthermore, the proposed framework indicates which resources have the most impact on the final selection of projects; therefore, the managers can analyze the decision of extending these resources. Finally, the procedure presented here, considers the uncertainties in an easy-to-understand method while being efficient and applicable.

The rest of the paper is organized as follows. The relevant literature is reviewed in Section 2. The preliminaries for the PROMETHEE method as well as its modified version to handle uncertain data are given in Section 3. The proposed framework and its modules are described in Section 4. The proposed method is implemented for a real case study and the corresponding results are discussed in Section 5. Finally, Section 6 concludes this paper.

2. Literature review

Project portfolio selection has been discussed by many researchers for more than 40 years. The reasons that attract researchers to this topic for such a long period of time could be the following (Iamratanakul, Patanakul, & Milosevic, 2008):

- Project portfolio selection is always a challenging issue for R&D and product development departments. Even though many researchers have already done various works, the nature of the topic is very broad such that there are always opportunities for future research.
- The research on project portfolio selection can be applied to other similar areas such as technology selection. In fact, the project and technology selection are similar topic where their processes and applications are sometimes interchangeable.
- The topic itself has some impact on a wide range of practices.

The project selection research can be categorized based on the two perspectives: fields of application and solution methods. Project selection is implemented in a wide variety of fields. For example, Chiadamrong (1999) presented an integrated fuzzy multi-criteria decision making method for manufacturing strategies selection. Kim, Park, and Seo (1997) proposed a matrix approach for telecommunications technology selection. Vieira Jairo, Khator, and Stange (1996) developed a portfolio selection model through mathematical programming in CAD environment. Lesusky, Rhudy, and Wiginton (1987) developed a knowledge-based system for information systems project development consulting. Park, Park, and Ntuen (1990) presented an integrated economic and strategic approach for investment decisions. Blasak and Ganti (1987) used a model to select microcomputer applications for hospital management. Fitzpatrick and Askin (2005) used their model to form effective worker teams. However, categorizing the research based on fields of application is not the focus of this section; instead, the presented solution methods will be discussed in the following.

Traditional project selection approaches would focused mainly on quantitative tools, such as discounted cash flow, net present value (NPV), return on investment (ROI) and payback period (Liberatore, 1987). However, these approaches ignore multiple factors impacting the project selection, and do not provide a useful transformative formula to combine all relevant criteria into a single decision making model (Brewer, Gatian, & Reeve, 1993). Therefore, multiple-criteria scoring and ranking methods are widely employed to improve project selection in businesses. These methods are used to score projects with respect to each of the evaluation objectives. Each objective is assigned a weight, and each project is scored with respect to the objectives (Chen & Cheng, 2009).

Iamratanakul et al. (2008) summarized the past and the present literature on project portfolio selection. They highlighted six groups of project portfolio selection methods including: benefit measurement methods, mathematical programming approaches, simulation and heuristics models, cognitive emulation approaches, real options, and ad hoc models. They report that each methodology does not address all of project portfolio selection aspects because each of which has its own advantages and disadvantages. For more information about the project portfolio selection models, the interested reader is referred to Graves and Ringuest (2003) and Iamratanakul et al. (2008). Fig. 1 shows the categorization of project portfolio selection models presented by Iamratanakul et al. (2008).

Surprisingly, although there is inherent uncertainty when determining the different input data like performance values (PVs) and criteria weights (CWs), but little attention has been paid to address the project selection process under uncertainty. At below, we present the most relevant research works dealing with uncertainty in the project selection area.

Charnes and Stedry (1966) proposed a technique named as chance-constrained programming model in which random variables are defined to consider uncertainty for availability of facilities that are required for performing R&D projects. But, other kinds of uncertainties are not considered in this method. Li (2009) considered budget uncertainty in highway investment decision making using a stochastic optimization model that explicitly addresses budget uncertainty in highway investment decision making. Li and Madanu (2009) presented an uncertainty-based methodology for highway project level life-cycle benefit/cost analysis and project evaluation. They analyzed project benefits by three approaches: deterministic, risk-based, and uncertainty-based ones. Then, the three sets of estimated project benefits are implemented in a stochastic optimization model for project selection. They showed that there are significant differences with and without uncertainty considerations. Li and Sinha (2004) presented another methodology for highway investment decision making under uncertainty that uses Shackle's model for uncertainty-based project benefit analysis and system optimization for project selection. Shackle's model overcomes limitations of the risk-based life-cycle cost analysis approach by using degree of surprise as a measure of uncertainty associated with possible outcomes of performance measures utilized for project benefit analysis. By presenting a case study, they revealed significant differences in project selection results using the proposed methodology versus the existing risk-based approach. Wey (2008) considered uncertainty of available budget, the chance of success and the efficient allocation of the project team in the urban renewal projects selection. Three techniques are integrated: integer-constrained multi-objective optimization, Monte Carlo simulation, and the Analytic Network Process where the probability distributions are used to describe costs. Medaglia et al. (2007) considered project selection as a stochastic multi-objective linearly-constrained optimization. They proposed an evolutionary method with partially funded projects, multiple (stochastic) objectives, project interdependencies (in the objec-

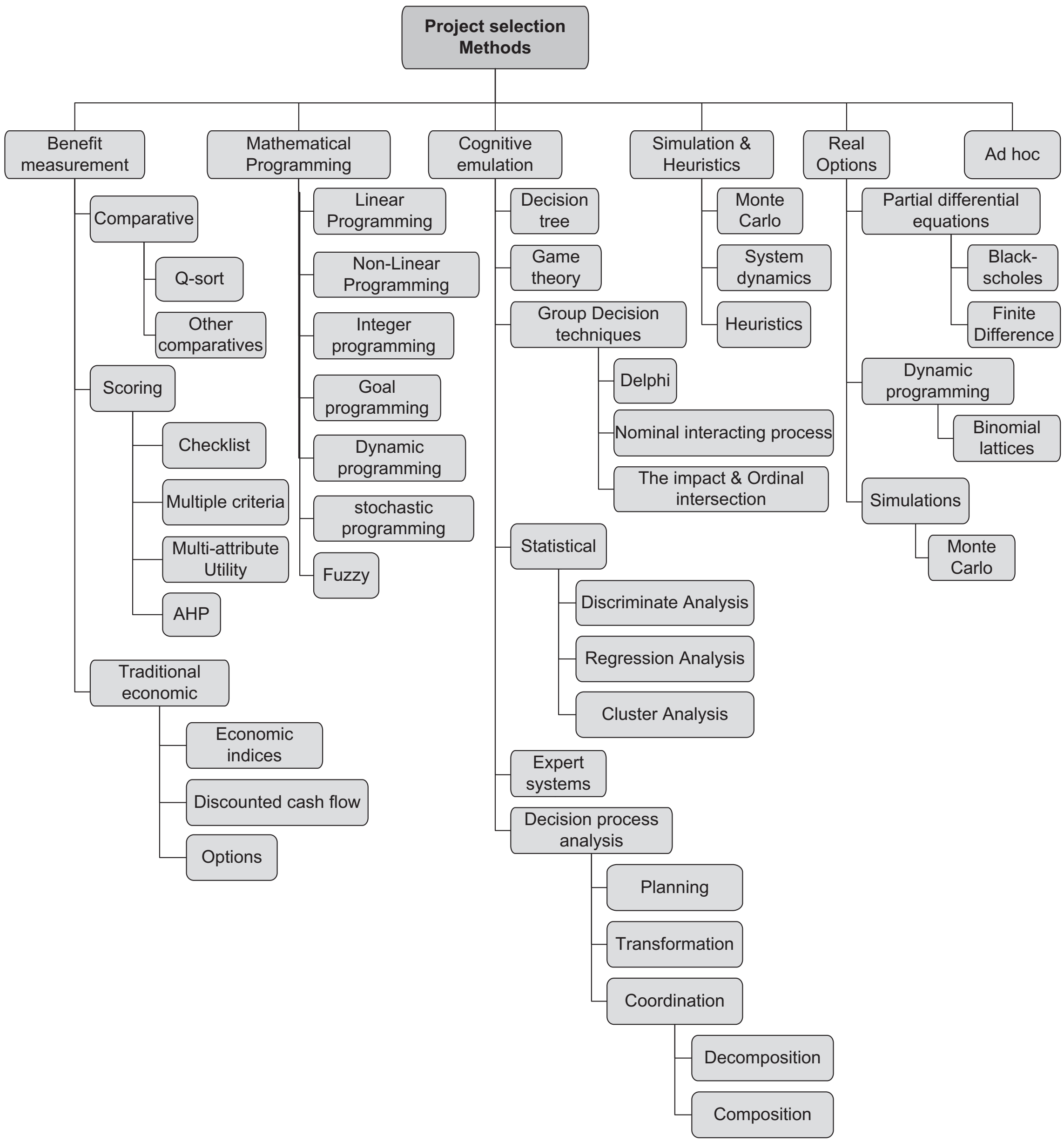

Fig. 1. A classification of project portfolio selection models (Iamratanakul et al., 2008).

tives), and a linear structure for resource constraints. This method is based on posterior articulation of preferences and is able to approximate the efficient frontier composed of stochastically non-dominated solutions. They compared the method with the stochastic parameter space investigation method (PSI) and illustrated it with a R&D portfolio problem under uncertainty based on Monte Carlo simulation.

As mentioned before, little attention has been paid so far to consider different kinds of uncertainties in the project selection process simultaneously. Some researchers (specially Medaglia et al., 2007), have tried to consider uncertainty in the project selection problem in a comprehensive way; but from the practical point of view, such models add complexity to an already complex process, and the result may often be a loss of transparency to the decision maker, in contrary to the methods of MCDA (Stewart, 2005). So, in this paper we have tried to present a new procedure which uses the advantages and capabilities of the PROMETHEE method linked to a Monte Carlo simulation in order to consider and possibly make lower all kinds of uncertainties of project selection problem in an acceptable complexity level. In addition, our procedure incorporates an assignment phase under uncertainty which has been neglected in the most of previous relevant works. Also, two linear assignment models are proposed to aggregate the simulation results.

At below, we first give some preliminary introductions to PROMETHEE method and its variants under uncertainty and then go through the details of the proposed framework.

3. Preliminaries

3.1. PROMETHEE method

Several Multi-Criteria Decision Aid (MCDA) methods have been proposed in recent decades to help the decision makers in selecting the best alternatives. In the meantime, the PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations) family of outranking methods and their applications has attracted much attention from academics and practitioners (Behzadian, Kazemzadeh, Albadvi, & Aghdasi, 2010).PROMETHEE technique is one of the best known and most widely applied outranking method because it follows a transparent computational procedure and can be easily understood by actors and DMs (Georgopoulou, Sarafidis, & Diakoulaki, 1998).

The PROMETHEE method was developed by Brans (1982) and further extended by Vincke and Brans (1985). Recently, Behzadian et al. (2010) have presented a comprehensive literature review in order to uncover, classify, and interpret the current research on PROMETHEE methodologies and applications. They classified the application areas into Environment Management, Hydrology and Water Management, Business and Financial Management, Chemistry, Logistics and Transportation, Manufacturing and Assembly, Energy Management, Social, and Other Topics.

The PROMETHEE is based on developing a preference function $P_j(a,b)$ which is a function of the difference d_j between the ratings of two alternatives for every criterion j (for example: $d_j = f(a,j) - f(b,j)$, where $f(a,j)$ and $f(b,j)$ are performance values of alternatives a and b regarding to criterion j, respectively). Then, a specific preference function is defined for each criterion and is used to determine the degree of preference, $P_j(a,b)$. Fig. 2 shows six general preference functions suggested by Brans, Vincke, and Mareschal (1986). Indifference q and preference p threshold values may also have to be defined for selected preference function.

Then, the multi-criterion preference index, $\prod(a,b)$, is defined as the average of the preference functions as follows:

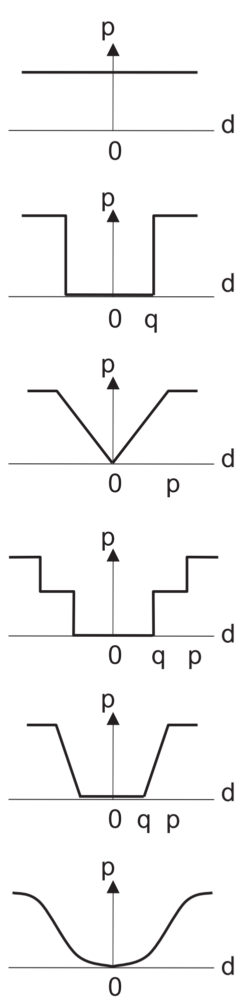

Fig. 2. General preference functions (Hyde et al., 2003).

$$\prod(a,b) = \frac{\sum_{j=1}^{J} w_j P_j(a,b)}{\sum_{j=1}^{J} w_j} \tag{1}$$

where w_j is the weight assigned to the criterion j. After that, two outranking indices, i.e., the positive and negative flows are defined for alternative a regarding to all alternatives, set A:

$$\phi^+(a) = \sum_A \prod(a,b) \quad \text{(positive flow)} \tag{2}$$

$$\phi^-(a) = \sum_A \prod(b,a) \quad \text{(negative flow)} \tag{3}$$

where $\phi^+(a)$ denotes that how much the alternative a is dominating other ones and $\phi^-(a)$ shows that how much the alternative a is dominated by the others. In this way, the total outranking value, net flow, is then determined by:

$$\phi(a) = \phi^+(a) - \phi^-(a) \tag{4}$$

Notably, some variations of the PROMETHEE method have been developed while they differ in the type of dealing with flow indices and their output. PROMETHEE I provides a partial ranking, including possible incompatibilities while PROMETHEE II shows a complete ranking of alternatives. PROMETHEE V extends the application of the PROMETHEE II in which the several options can be selected in respect to a set of constraints. Another variant in this family is the PROMETHEE GAIA, a geometrical analysis tool for interactive aid, which presents the results in a geometrical plane with the aim of reducing the multi-dimensional criteria space to a two-dimensional criteria plane which allows direct visual presentation of the results.

3.2. PROMETHEE under uncertainty

A DM is faced with two kinds of uncertainties when using the PROMETHEE method: assignment of PVs and elicitation of CWs. PVs are assigned by experts to each criterion for each alternative. Generally, the DM does not have a full knowledge and access to the alternatives being assessed because they are predicted future events or out of the reach. So, there may be some imprecision, contradiction, arbitrariness and/or lack of consensus in determining PVs. PROMETHEE has tried to take these uncertainties into account by defining and using general preference functions but DM encounters another kind of uncertainty in selecting the proper preference function and defining preference and indifference thresholds (Salminem, Hokkanen, & Lahdelma, 1998). CWs are the other inputs that add another kind of uncertainty to the decision making process; especially when there are multiple DMs.

Hyde, Maier, and Colby (2003) introduced a stochastic method to incorporate uncertainty in the decision making process. In this way, uncertainty in the input data, i.e., PVs and CWs, are defined using probability distributions. Then, a reliability analysis by using Monte Carlo simulation is performed. Finally, a significance analysis is undertaken using the Spearman rank correlation coefficient. This method is employed in this paper in order to deal with uncertainties in the PROMETHEE part of the proposed procedure for project selection.

4. Proposed project selection framework

The proposed framework involves six stages including the: problem definition, Monte Carlo simulation I, improvement of uncertainty level, ranking aggregation, Monte Carlo simulation II along with the final allocation as well as a sensitivity analysis on constraints. Fig. 3 shows the structure of our framework and the interaction between its stages. It is not required to determine thresholds if a probability distribution function is fitted or defined

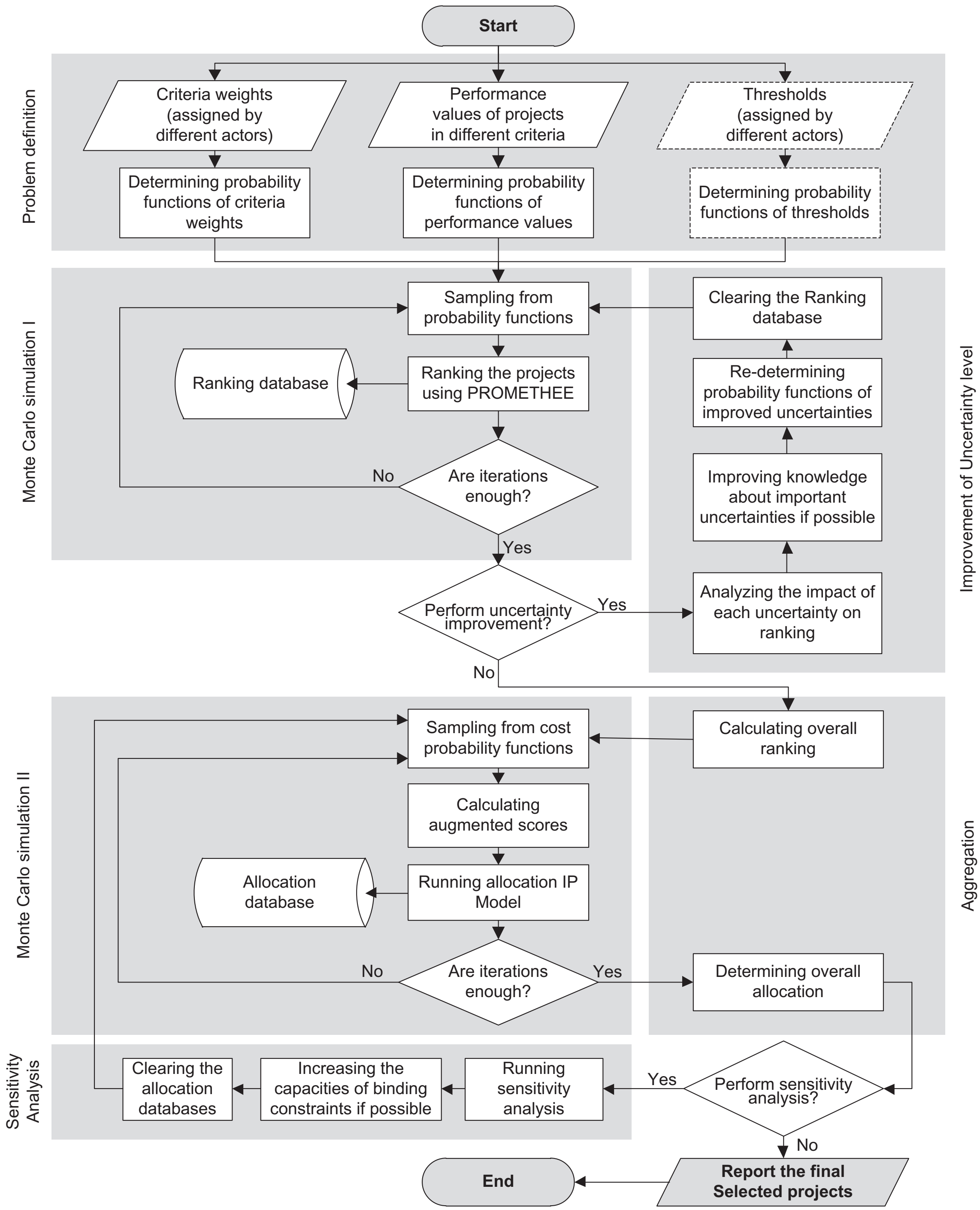

Fig. 3. The structure of proposed framework.

for each criterion but if there is enough knowledge to deterministically set performance values in one or more specific criterion/criteria; a proper preference function should be selected, like Fig. 2, and the preference thresholds should be set as well (Hyde et al., 2003). That is why the determination of thresholds and their distributions are shown by dashed lines in Fig. 3.

4.1. Problem definition

Problem definition is the first stage in every multi-criteria decision making problem. Problem definition is handled by experts and actors. Actors are some authorities, directly or indirectly involved in the policy making process and groups of people affected by decisions. Briefly, we can mention the following steps for this stage:

- Identifying the actors.
- Defining the projects ($P_1, P_2, \ldots, P_n$).
- Defining the criteria ($C_1, C_2, \ldots, C_m$).
- Providing the criteria weights by actors ($w_1, w_2, \ldots, w_m$).
- Assigning the criteria performance values of projects by experts (x_{ij}).
- Fitting the most appropriate probability distributions to actual input data or defining them based on decision makers' knowledge.

Defining proper criteria is highly dependent to the kind of projects (e.g., information systems, construction or R&D project types) and stakeholders' utilities. Many researchers have suggested different criteria for specific project selection problems. Buss (1983) considered intangible benefits, technical importance, and degree of compatibility with corporate objectives for ranking computer projects. Henriksen and Traynor (1999) defined relevancy, risk, reasonableness and return criteria for ranking R&D projects. Liang and Li (2008) defined detailed criteria for enterprise information system project selection and categorized them into the four categories, i.e., benefits, opportunities, costs and risks.

In the situations where relatively a large number of actors are involved in the decision making process, the CWs of the actors can be considered as a representative sample of the CWs of the stakeholders' population. Then, goodness of fit statistics is used to determine the best fitted distributions. But, in the situations that a small number of actors are involved, either a normal or uniform distribution can be fitted to address the CWs (Hyde et al., 2003).

Performance values may be qualitative or quantitative. The uncertainty, imprecision and variability in the quantitative PVs can be indicated by the continuous probability distributions such as uniform, normal or logistic. The distribution can be defined by a range of values; for example, if we define a uniform distribution, we should set only its lower and upper bound. For qualitative criteria, a discrete uniform distribution can be utilized (Hyde et al., 2003).

As mentioned before, if DM has enough knowledge to deterministically set the performance values in one or more specific criterion/criteria; it is required to select a proper preference function and also set its preference thresholds. These thresholds can be either probabilistic or deterministic. If they are probabilistic, a proper probability distribution should be defined too.

4.2. Monte Carlo simulation I

Monte Carlo simulation method investigates the stochastic permutations of uncertainties. Each uncertainty is addressed by a proper distribution function. The Monte Carlo simulation method is done by running a number of iterations. At each iteration, a sample value is first extracted from each probability distribution. Then, the concerned analysis, here PROMETHEE method, is performed based on these sampled values. The output of this analysis is saved as a record. It is important to run sufficient iterations in order to have a valid simulation output. One way is to determine a specific number of iterations (i.e., 1000, 2000, 5000, and so on) by considering the size of projects and the importance of risks. Another way is to stop the simulation process when the sampled values are able to fit the probability distribution which they have been extracted from. For the situations where there are dependencies between PVs, it is suggested to use the method proposed by Rezaie, Amalnika, Gereie, Ostadi, and Shakhseniaeea (2007) and Rezaie, Gereie, Ostadi, and Shakhseniaee (2009) which considers the dependencies while sampling the values in order to provide feasible sampled values.

4.3. Improvement of uncertainty level

It is beneficial to make lower the uncertainty level in every decision making parameter (i.e., CWs and PVs). Some parameters related to some activities or processes have uncertainty in their nature and it is not possible to significantly lower their uncertainty level. But, others can be lowered by revising them via enhancing of DM's knowledge. A key aspect that should be considered is to concentrate on those parameters which have the most impact on project rankings. Some parameters have a little impact on rankings and it is not worthy to work on them. Hyde et al. (2003) used significance analysis to identify the relative contribution of each input parameter when determining the ranking of projects. The most significant inputs are determined using the Spearman rank correlation coefficient as follows (Kottegoda & Rosso, 1997):

$$R = 1 - \left(\frac{6\sum_{i=1}^{d} D_i^2}{d(d^2 - 1)} \right) \tag{5}$$

where d is the total number of records (simulation iterations), and D_i is the difference between the rank of total flow of a specific alternative and the rank of a specific input parameter in iteration i. The value of R lies between -1 and +1. The values of +1 and -1 indicate significant impact of considered parameter on the projects' ranking. When R is close to zero, it is concluded that the parameter does not have significant impact on the ranking. In this way, those parameters that have the most impact on projects' ranking are refined by collecting more data, where it is possible, to reduce the level of their uncertainty.

4.4. Calculating the overall ranking

Running the Monte Carlo simulation I results in many records. Thus, it is needed to aggregate these records and assigning a unique rank to each project. A linear assignment model is proposed to aggregate the simulation records.

Accordingly, we first use the 'Ranking' database to report the probability of different ranks that a project can achieve. For example, consider four projects that have been analyzed via 1000 simulation iterations. Assume that project 1 has achieved ranks 1 (worst), 2, 3, and 4 in 650, 210, 130, and 10 iterations, respectively. If we denote P_{ij} as the probability that project i can achieve rank j; we have: P_{11} = 0.65; P_{12} = 0.21; P_{13} = 0.13; P_{14} = 0.01.So, P_{ij} is calculated as follows:

$$P_{ij} = \frac{\text{The number of iterations that project } i \text{ has achieved rank } j}{\text{Total number of iterations}} \tag{6}$$

Then, the following linear assignment model is adopted in order to determine the overall rank of each project (i.e., the most appropriate rank), based on the ranks probabilities extracted from the simulation study:

$$\begin{aligned} &\text{Maximize } Z = \sum_i \sum_j P_{ij}.x_{ij} \\ &\text{Subject to} \quad \sum_j x_{ij} = 1 \quad i = 1, 2, \ldots, n \\ &\qquad \sum_i x_{ij} = 1 \quad j = 1, 2, \ldots, n \\ &\qquad x_{ij} \in \{0, 1\} \end{aligned} \tag{7}$$

where x_{ij} = 1 denotes that the overall rank of project i is considered as j.

4.5. Monte Carlo simulation II

Because the required costs of each project are stochastic, another Monte Carlo simulation is carried out to make possible performing the two next modules of the proposed framework, i.e., calculating the augmented scores and running the allocation IP model. Notably, the augmented scores will be used in the objective function of the allocation IP model. The allocations resulted by the allocation IP model are stored in the allocation database which in turn will be used when calculating the overall allocations, as described in Section 4.5.2.

4.5.1. Calculating the augmented scores

A common way to deal with both the multiple-criteria and given constraints in a project selection problem is to use a two-phase approach where a multi-criteria evaluation of the projects is first carried out using an MCDA method that accounts for both the qualitative and quantitative criteria for calculating the final score of each project, and then this information are utilized in the objective function of an integer programming (IP) model that is able to incorporate the real-world constraints (see e.g., Abu-Taleb & Mareschal, 1995; Golabi, Kirkwood, & Sicherman, 1981; Mavrotas, Diakoulaki, & Capros, 2003). In these combined approaches, the projects' scores resulting from the first stage of the analysis are often used in an additive objective function that drives the IP model. Usually, the IP model has a knapsack form in the form of maximizing the aggregated performance function of a combination of projects subject to a budget constraint along with multiple side constraints.

In most of relevant published papers, a mathematical programming model is performed as a portfolio optimizer, which is to maximize the aggregated performance of a combination of projects that comply with the imposed constraints. However, it is somewhat different in Mavrotas et al. (2008). That is, they do not try to maximize the aggregated performance function but to maximize the compatibility of the final selection with the initial ranking of the projects. The basic difference between the two concepts is attributed to the inevitable budget constraint that causes a bias towards selecting the low cost projects. They use a technique to overcome this problem by using the appropriately modified coefficients of the IP's objective function called augmented scores instead of initial scores.

Augmented scores (as) as proposed by Mavrotas et al. (2008), are calculated based on the rankings reported by MCDA technique. The augmented score for ith project (i.e., p_i) has the property that no combination of projects which are lower in the rank and need lower budget than p_i can have an augmented score greater than p_i's augmented score. In order to find the augmented scores, projects are sorted according to their multi-criteria score (ms) while the worst project is put in the first and the best project at the end. For the worst project, as is assigned to 1. Then, for the kth project ($k = 2, \ldots, n$), the following knapsack problem is solved in order to determine the z_k:

$$\begin{aligned} &\text{Maximize } z_k = \sum_{i=1}^{k-1} as_i.x_i \\ &\text{Subject to } \sum_{i=1}^{k-1} c_i x_i \leqslant c_k \\ &\qquad x_i \in \{0,1\} \end{aligned} \tag{8}$$

where c_i denotes the total cost of the project i. After determining z_k, if $z_k > as_{k-1}$ then $as_k = z_k + 1$; otherwise, $as_k = as_{k-1} + 1$. Fig. 4 shows the flowchart of this algorithm. Noteworthy, as shown in Fig. 3, calculation of augmented scores is done as a part of the Monte Carlo Simulation II in order to have different augmented scores in each iteration.

4.5.2. Allocation IP model

The IP model proposed by Mavrotas et al. (2008) is adopted here. In order to overcome the bias in selection phase, the model has only one objective function with the augmented scores as its coefficients:

$$\text{Maximize } z = \sum_{i=1}^{n} as_i.x_i \tag{9}$$

where x_i is 1 if the project i is selected, otherwise, it is zero. Moreover, the constraints of IP model are defined regard to the DM's available information and preferences. For example, a segmentation constraint may be expressed as "no more than 50% of the selected projects must belong to subset A" or "at least 30% of the selected projects should belong to subset B". These two sample constraints can be, respectively, modeled as:

$$\begin{aligned} &\sum_{i \in S_A} x_i \leqslant 0.5 \sum_{i=1}^{n} x_i \\ &\sum_{i \in S_B} x_i \geqslant 0.3 \sum_{i=1}^{n} x_i \end{aligned} \tag{10}$$

Moreover, an example for logical constraint could be: "projects 3 and 4 are mutually exclusive" or "if project 2 is selected, then project 1 must be selected as well". These two logical constraints can be defined as:

$$\begin{aligned} &x_3 + x_4 \le 1 \\ &x_2 - x_1 \le 0 \end{aligned} \tag{11}$$

And finally, the cost constraint is defined as:

$$\sum_{i=1}^{n} c_i x_i \leqslant budg \tag{12}$$

where $budg$ is the total available budget. The output of this allocation IP model in different simulation iterations are stored in the allocation database and will then be used when calculating the overall allocation, as described in Section 4.6.

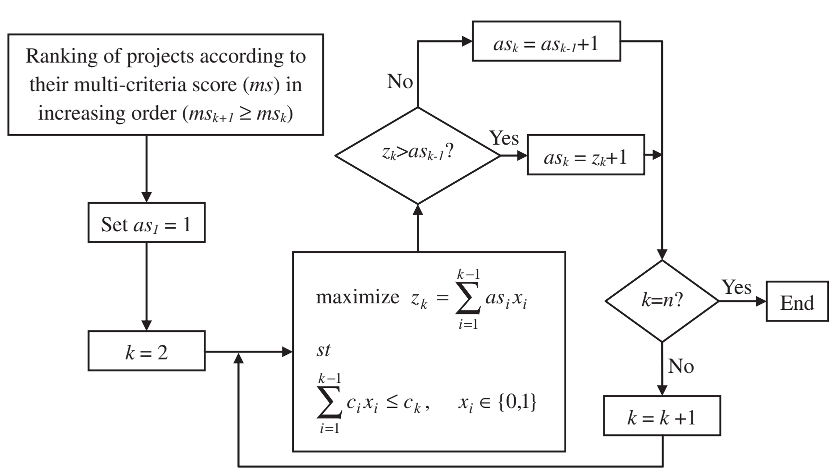

Fig. 4. Flowchart of the algorithm for calculating the augmented scores (Mavrotas et al., 2008).

Table 1
The probability distributions of the criteria weights.

Cost	Methodology	Personnel	Sci. & Act. Cap.	Technical Cap.
0.231	0.141	0.143	0.122	0.363
0.223	0.129	0.130	0.114	0.404
0.172	0.140	0.157	0.149	0.382
0.231	0.120	0.129	0.122	0.398
0.167	0.141	0.126	0.132	0.434
0.213	0.140	0.119	0.115	0.413
0.193	0.139	0.132	0.118	0.418
0.225	0.139	0.144	0.124	0.368
0.214	0.134	0.140	0.136	0.376
0.182	0.133	0.144	0.142	0.399
0.16 + 0.08 * BETA(0.908, 0.702)	0.11 + 0.04 * BETA(7.94, 4.56)	0.11 + ERL(0.004, 6)	TRI(0.11, 0.115, 0.16)	0.35 + 0.1 * BETA(1.68, 2.01)

4.6. Determining the overall allocation

Similar to the Monte Carlo simulation I, the second Monte Carlo simulation generates many records. Thus, it is needed to assign a unique decision, selected or not, to each project.

To do so, we first use the 'Allocation' database and report K_i, the number of iterations that the project i has been selected by IP model. In this way, the projects with bigger K_i are most likely to be selected. Then, we use the following objective function subject to all constraints of the allocation IP model. In this way, the constraints of the allocation IP model will be satisfied while at the same time those projects which have previously been selected in most of the simulation runs, are finally selected:

$$\begin{aligned} &\text{Maximize } Z = \sum_i x_i K_i \\ &\text{Subject to} \quad \text{The constraint(s) of IP allocation model} \\ &\qquad\qquad x_i \in \{0,1\} \end{aligned} \tag{13}$$

4.7. Sensitivity analysis on allocation IP model

A supplementary sensitivity analysis can be done on the final (overall) allocation IP model. In this way, we can interpret the dual prices as the effect of constraints, especially budget constraint, on the objective function and try to change the resources in order to widen the final selection list.

Table 2
The performance values of the projects.

Project	Type	Cost	Method.	Personnel	Sci. & Act.	Tech. Cap.
Project 1	Applied	341–447	4–8	3–6	2–5	3–7
Project 2	Basic	31–42	5–8	2–4	3–5	0–1
Project 3	Applied	316–493	3–5	4–6	4–6	2–4
Project 4	Applied	351–496	5–7	0–2	2–5	0–2
Project 5	Developing	142–161	5–9	4–6	3–7	3–5
Project 6	Applied	387–420	3–8	2–4	1–4	2–6
Project 7	Basic	33–45	5–10	1–5	0–1	1–5
Project 8	Developing	101–183	1–3	2–7	3–7	1–4
Project 9	Basic	33–44	0–5	2–3	1–6	1–2
Project 10	Applied	393–453	0–4	2–4	3–4	3–5
Project 11	Applied	307–436	3–7	0–2	2–3	1–4
Project 12	Basic	37–48	2–7	2–4	0–3	1–6
Project 13	Basic	35–47	2–5	5–9	5–9	1–6
Project 14	Basic	35–46	3–6	2–4	2–3	1–5
Project 15	Developing	145–188	2–6	4–8	4–5	1–4
Project 16	Applied	374–486	2–6	4–8	1–3	2–6
Project 17	Basic	35–44	1–4	1–3	5–8	0–3
Project 18	Applied	330–452	0–3	2–4	3–6	1–3
Project 19	Developing	138–151	0–2	4–8	2–4	1–5
Project 20	Applied	307–432	3–4	0–2	4–7	2–5
Project 21	Applied	325–405	4–7	4–6	3–5	1–5
Project 22	Basic	39–50	1–5	5–6	3–8	3–4
Project 23	Basic	37–49	4–7	0–4	1–3	1–6
Project 24	Applied	385–416	1–4	1–4	1–5	3–5
Project 25	Applied	318–441	3–6	2–4	1–4	1–4
Project 26	Basic	37–45	1–3	1–2	1–5	4–9
Project 27	Applied	315–467	2–7	3–8	2–5	5–10
Project 28	Basic	32–46	2–6	1–5	4–9	4–6
Project 29	Developing	129–171	3–6	1–5	2–5	4–6
Project 30	Applied	328–476	5–8	3–4	4–6	4–5
Project 31	Applied	385–464	1–6	1–2	4–7	4–8
Project 32	Applied	304–493	3–6	3–6	2–4	3–6
Project 33	Applied	310–403	0–2	2–3	3–5	1–3
Project 34	Developing	106–166	4–7	3–7	1–4	4–7
Project 35	Applied	322–490	2–6	4–8	5–8	3–5
Project 36	Applied	367–489	2–4	3–8	5–10	1–6
Project 37	Basic	36–46	0–4	3–7	1–4	4–6
Project 38	Basic	33–46	3–6	4–9	5–8	3–5
Project 39	Basic	32–49	3–5	3–6	1–6	4–6
Project 40	Developing	145–158	0–3	4–8	2–6	2–4

5. Case study

Iran Telecommunication Research Center, ITRC, as the most experienced research entity in the Information and Communication Technology field, with more than 39 years of scientific experience in research and acting as major consultant to the Ministry of ICT, is the main ICT research base in Iran. ITRC boasts highly experienced researchers, advanced research facilities as well as dedicated laboratories that enable research teams to conduct their studies and carry out experiments, under four broad faculties: Information Technology, Communication Technology, ICT Security, and Strategic and Economical Studies.

Generally, many research projects are proposed to ITRC and they should select the most appropriate projects among them. Three types of projects can be defined as: basic, developing, and applied projects. Each type has a budget limit. Five criteria are used to evaluate the projects as follows:

- Cost: Total project cost including all expenses required for project completion.
- Proposed methodology: Degree of being step-by-step, well-planned, scientifically-proven, disciplined, and proper for organization current status in the proposed methodology.
- The abilities of personnel: Work experience of project team related to concerned project.
- Scientific and actual capability: Scientific degree and educational certificates of project's team.
- Technical capability: Ability of providing technical facilities and infrastructures.

Ten actors are involved to set criteria weights. The probability distribution of weights is fitted using input analyzer module of Arena 7. Table 1 shows the assigned weights and their best fitted probability distributions. In this way, the probability distributions of the above criteria are respectively fitted to Beta, Beta, Erlang, Triangular, and Beta with the parameters and offset values presented in the last row of Table 1.Then, 5000 sample data are generated for each fitted distribution which are then used in the Monte Carlo simulations.

Performance values of 40 specific projects are determined as uniform distributions with min and max probable values as shown in Table 2. The project types have also been mentioned in Table 2. For example, projects 1, 2, and 5 are of applied, basic, and developing types, respectively.

After performing the Monte Carlo simulation I, Spearman rank correlation coefficient is used to calculate the impact of different uncertainties on the projects ranking. This analysis indicates those uncertainties which have the most impact on the project rankings. Figs. 5 and 6 show this analysis for all projects and only for project 4, respectively. As shown in Fig. 6, the performance values in the criteria 1, 2, and 4 have the most impact, about 63%, on the respective ranking. So, if possible, lowering these three uncertainties will significantly affect the final ranking. Furthermore, the experts can work more on the uncertainties to lower the uncertainty level in general.

Overall ranking of each project is determined by implementing the proposed linear assignment optimization model. The projects are sorted from the worst to the best in order to determine the augmented scores. Table 3 shows the calculated augmented scores in regard to sampled costs at one iteration. Bold items in Table 3 show the states where Z_k is greater than as_{k-1} and a jump is happened in the augmented scores. The allocation IP module creates each record of allocation database. Four constraints have been considered for our case study. Eq. (14) enforces the allocated budget to be satisfied; which is 6000 million Toomans (Iranian monetary unit) for the "IT Strategic management and governance" unit. Eqs. (15)–(17) imply the segmentation constraints. In this way, 60, 10, and 30 percentages of the given project portfolio are selected among the applied, basic, and developing candidate projects, respectively.

$$\sum_{i=1}^{n} c_i x_i \leqslant 6000 \tag{14}$$

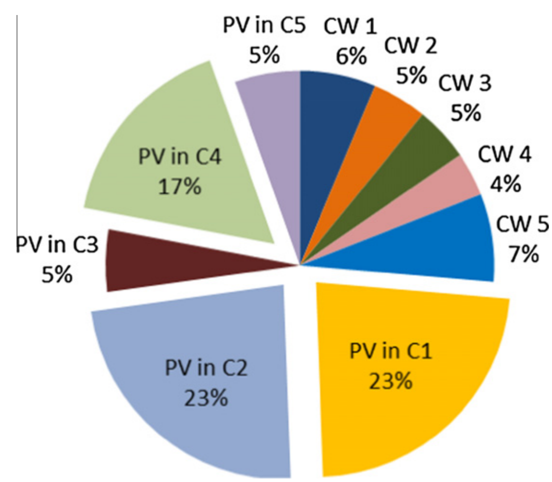

Fig. 6. The impact of uncertainties on project 4.

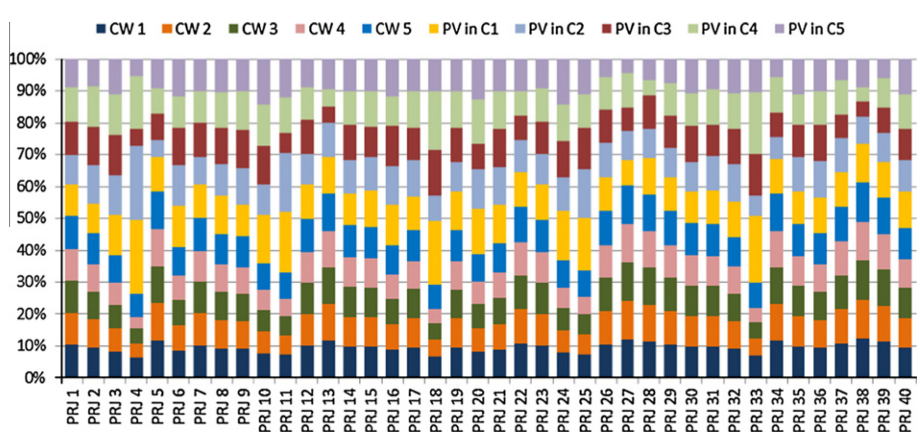

Fig. 5. The impact of uncertainties on ranking of projects.

$$x_2 + x_7 + x_9 + x_{12} + x_{13} + x_{14} + x_{17} + x_{22} + x_{23} + x_{26} + x_{28} + x_{37} + x_{38} + x_{39} \leqslant 0.1 \sum_{i=1}^{n} x_i \quad (15)$$

$$x_5 + x_8 + x_{15} + x_{19} + x_{29} + x_{34} + x_{40} \leq 0.3 \sum_{i=1}^{n} x_i \quad (16)$$

$$x_1 + x_3 + x_4 + x_6 + x_{10} + x_{11} + x_{16} + x_{18} + x_{20} + x_{21} + x_{24} + x_{25} + x_{27} + x_{30} + x_{31} + x_{32} + x_{33} + x_{35} + x_{36} \leq 0.6 \sum_{i=1}^{n} x_i \quad (17)$$

Table 4 shows the first five records of allocation database where the selected projects have been shown with the star marks. This table also shows the number of iterations that each project has been selected by the IP model, K_i. After that, the overall allocation is determined via the IP model (13). Table 5, shows the final solution with the average cost equal to 5796.5 million Toomans. Final solution includes 12 applied, 2 basic, and 6 developing projects. The modules have been coded in MATLAB and an optimization toolbox is used for running of all optimization modules, i.e., the overall ranking model (7), the augmented scores model (8), the allocation IP model (9, 14–17) and the overall allocation model (13). The process time for 5000 iterations of simulation I and 100 iterations of

Table 3
The calculated augmented scores according to the sampled costs in an iteration.

Project	as_k	c	Z_k
Project 4	1	423.5	-
Project 33	2	356.5	0
Project 18	3	391	2
Project 11	4	371.5	2
Project 25	5	379.5	4
Project 10	6	423	5
Project 24	7	400.5	5
Project 20	8	369.5	2
Project 21	9	365	2
Project 16	10	430	9
Project 3	11	404.5	9
Project 9	12	38.5	0
Project 6	22	403.5	**21**
Project 36	23	428	22
Project 8	24	142	12
Project 32	37	398.5	**36**
Project 2	38	36.5	0
Project 31	75	424.5	**74**
Project 7	76	39	38
Project 14	77	40.5	76
Project 17	78	39.5	76
Project 15	270	166.5	**269**
Project 35	552	406	**551**
Project 30	553	402	551
Project 40	554	151.5	231
Project 1	941	394	**940**
Project 19	942	144.5	193
Project 23	943	43	78
Project 26	944	41	78
Project 29	1966	150	**1965**
Project 12	1967	42.5	944
Project 22	1968	44.5	1967
Project 13	1969	41	944
Project 37	1970	41	1969
Project 34	5908	136	**5907**
Project 5	5909	151.5	5908
Project 28	5910	39	76
Project 39	5911	40.5	5910
Project 27	25,604	391	**25,603**
Project 38	25,605	39.5	5910

Table 4
The summary of allocation database.

Project	The first five records					K_i
	1	2	3	4	5	
Project 1	*	*	*	*	*	100
Project 2						0
Project 3	*	*	*	*	*	100
Project 4						0
Project 5	*	*	*	*	*	100
Project 6	*	*	*	*	*	100
Project 7						0
Project 8						0
Project 9						0
Project 10						0
Project 11						0
Project 12						0
Project 13						0
Project 14						0
Project 15	*	*	*	*	*	100
Project 16	*	*	*	*	*	98
Project 17						0
Project 18						1
Project 19	*	*	*	*	*	100
Project 20	*	*		*	*	94
Project 21	*	*	*	*	*	99
Project 22						0
Project 23						0
Project 24					*	3
Project 25			*			6
Project 26						0
Project 27	*	*	*	*	*	100
Project 28						1
Project 29	*	*	*	*	*	100
Project 30	*	*	*	*	*	100
Project 31	*	*	*	*	*	100
Project 32	*	*	*	*	*	100
Project 33						1
Project 34	*	*	*	*	*	100
Project 35	*	*	*	*	*	100
Project 36	*	*	*	*		98
Project 37						0
Project 38	*	*	*	*	*	100
Project 39	*	*	*	*	*	99
Project 40	*	*	*	*	*	100

Table 5
The final selected projects.

Project	Cost		Type
	L.B.	U.B.	
1	341	447	Applied
3	316	493	Applied
5	142	161	Developing
6	387	420	Applied
15	145	188	Developing
16	374	486	Applied
19	138	151	Developing
20	307	432	Applied
21	325	405	Applied
27	315	467	Applied
29	129	171	Developing
30	328	476	Applied
31	385	464	Applied
32	304	493	Applied
34	106	166	Developing
35	322	490	Applied
36	367	489	Applied
38	33	46	Basic
39	32	49	Basic
40	145	158	Developing
Total average cost:	5796.5		

simulation II was about 38 min which seems to be reasonable when running a real case. Notably, two optimization modules, i.e., the one for calculating the augmented scores and the IP allocation model, are run in each iteration of the Monte Carlo simulation II. Consequently, the computation time could be considerable for the large number of iterations. Accordingly, we first tried for 1000 iterations which took nearly 6 h of CPU time in our case study. Then, we performed only 100 iterations which only took about 35 min of CPU time and when we checked the results of these two different runs, we observed the same results. So, we chose 100 iterations as an acceptable number of iterations for the Monte Carlo simulation II.

It should be noted that the sensitivity analysis on constraints could be easily done in general using the well-known concepts and methods given in the duality theory, but in our case study it could not be performed since the allocated budget was fixed and could not be changed. Also, the segmentation ratios, 0.1, 0.3, and 0.6, were defined in our case as a fixed values based upon the management's policies and priorities.

Furthermore, it was interesting to perform a comparison between our proposed approach and its deterministic counterpart. For this, the mean of each distribution function were considered as the deterministic case followed by determining the overall ranking, the augmented scores, and the overall allocation deterministically by using the method proposed by Mavrotas et al. (2008). Table 6 shows this comparison which implies the significant differences between the results. The main reason for justifying these different results can be regarded to simplifying assumption of determining a unique value for the problem inputs in the deterministic case while even the small changes in these values will significantly changes the overall ranking.

Table 6
The comparative results of deterministic and stochastic models.

Project	Selection decision	
	Deterministic	Stochastic
Project 1	*	*
Project 2		
Project 3		*
Project 4	*	
Project 5	*	*
Project 6	*	*
Project 7		
Project 8	*	
Project 9	*	
Project 10	*	
Project 11	*	
Project 12		
Project 13		
Project 14		
Project 15	*	*
Project 16		*
Project 17		
Project 18	*	
Project 19	*	*
Project 20	*	*
Project 21	*	*
Project 22		
Project 23		
Project 24	*	
Project 25	*	
Project 26		
Project 27		*
Project 28		
Project 29	*	*
Project 30		*
Project 31		*
Project 32		*
Project 33	*	
Project 34	*	*
Project 35		*
Project 36	*	*
Project 37		
Project 38		*
Project 39	*	*
Project 40		*
Total	20	20

6. Conclusion

A comprehensive framework for project selection under uncertainty is proposed in this paper. This framework is able to incorporate the real-world constraints and accounts for all possible kinds of uncertainties in the project selection problem, i.e., those in the performance values (PVs), criteria weights (CWs) and preference thresholds. The PROMETHEE method is embedded into a Monte Carlo simulation framework in order to rank the projects under uncertainty. The output of simulation is used to determine the probabilities of achieving different ranks by each project and also to analyze the impact of different uncertainties on the final ranking. A linear assignment model is proposed to calculate the overall ranking amongst all simulation iterations. Overall ranking is then used to determine the augmented scores, i.e., the coefficients of final selection model. The final selection model is an integer programming one that selects the most appropriate projects subject to segmentation, logical, and cost constraints. The IP model overcomes the bias against low cost combination of projects which is usually occurred in the knapsack-type formulation. The proposed framework is applied to a case study and the corresponding results are presented. The results have been compared with a deterministic approach which shows significantly different results. In summary, the main contributions of the proposed framework can be outlined as follows:

- Tackling both phases of project selection problem, i.e., the ranking and assignment phases.
- Linking the PROMETHEE method with Monte Carlo simulation to cope with all kinds of uncertainties; including those of related to performance values, criteria weights, and preference thresholds.
- Linking up the simulation-based PROMETHEE scores and assignment phase via the proposed linear assignment model.
- Linking the allocation IP model with another Monte Carlo simulation to cope with cost uncertainties in the assignment phase.
- Identifying the most important parameters which their uncertainty level need to be lowered as a result of uncertainty analysis.
- Enabling to detect those resource constraints which have the most effect on the project selection decision.

There are also several ways to extend this work. First, a comparative study between the final results of suggested model with the existing models in the literature seems to be interesting. Another suggestion is to address the parameters' uncertainties as fuzzy numbers instead of probability distributions for which all steps of the proposed framework must be adapted in a fuzzy environment. Preparing commercial software is another suggestion which is really beneficial for both academicians and practitioners.

Acknowledgements

We would like to express our sincere thanks for all helps rendered to us by the Iran Telecommunication Research Center (ITRC) during this study; specially Mr. Mahdi Fasanghari, the strategic manager of ITRC.

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