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International Journal of Project Management 30 (2012) 791 – 803

International Journal of Project Management

www.elsevier.com/locate/ijproman

A methodology for selecting portfolios of projects with interactions and under uncertainty

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Received 15 September 2010; received in revised form 18 January 2012; accepted 24 January 2012

Abstract

Effective project evaluation and selection strategies can directly impact organizational productivity and profitability. Numerous analytical techniques ranging from simple weighted scoring to complex mathematical programming approaches have been proposed to solve these problems. However, traditional project selection methods too often fail to consider both the uncertainties in projects and the interaction among projects. Some prior studies have considered the interaction among projects in deterministic environments. Others have dealt with stochastic environments but have not considered project interdependencies. This study aspires to fill this gap in the project portfolio selection literature. Information system/ information technology (IS/IT) projects are used in this study because they are frequently subject to uncertainties due to estimation difficulties and bounded by interactions due to technological interdependencies. We use Data Envelopment Analysis (DEA) to select the best portfolio of IS/IT projects while taking both project uncertainties (modeled as fuzzy variables) and project interactions into consideration simultaneously. We also present a numerical example to demonstrate the applicability of the proposed framework and exhibit the efficacy of the procedures.

Keywords: IS/IT project; Portfolio selection; Data envelopment analysis; Fuzzy set theory

1. Introduction

Many organizations have been increasing their investments in Information Systems/Information Technologies (IS/IT) to meet the growing demands for efficiency and effectiveness (Gunasekarana et al., 2001). Rivard et al. (2006) argue that well-planned IS/IT investments that are carefully selected with respect to business mission requirements can have a positive impact on organizational performance. Conversely, IS/IT investments that are poorly planned, can postpone or severely limit organizational performance (Gunasekarana et al., 2001). Farbey et al. (1999) have commented “There is concern that poor evaluation procedures mean it is difficult to select projects for investment, to control development and to measure business return after implementation [p. 189]”. Often organizations need to choose between a number of competing IS/IT investments for various reasons including limited resources and capacity constraints.

Many theoretical and practical models have been developed to support the process of project portfolio selection. Early attempts focused on constrained optimization methods were given a set of candidate projects; the goal is to select a subset of projects to maximize some objective function without violating the constraints (Danila, 1989). Some prior studies have considered the interaction among projects in deterministic environments (i.e. Bardhan et al., 2004; Eilat et al., 2006). Others have dealt with stochastic environments but have not considered project interdependencies (i.e. Chen and Cheng, 2009; Huang et al., 2008; Lin and Hsieh, 2004; Tiryaki and Ahlatcioglu, 2005, 2009). As a result, these models have not found widespread use in practice (Eilat et al., 2006). This study aspires to fill this gap in the project portfolio selection literature. We use Data Envelopment Analysis (DEA) to

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doi:10.1016/j.ijproman.2012.01.012

select the best portfolio of projects taking both project uncertainties (modeled as fuzzy variables) and project interactions into consideration simultaneously. Another contribution of this study is the application of fuzzy DEA (FDEA) for project portfolio selection. This approach has not been undertaken previously, and promises to enrich considerably the decision making technology.

IS/IT projects are Research and Development (R&D) projects with some distinctive features (Møen, 2005). However, IS/IT projects have certain attributes that differentiate them from the other types of R&D projects (Møen, 2005). For example, adoption of IS/IT initiatives can be more lengthy, expensive and complex (Gunasekarana et al., 2001). IS/IT investments also tend to have a high failure rate that might have potentially devastating impacts (Wu and Ong, 2008). One of the most critical characteristics of IS/IT investments that differentiates them from the other types of R&D projects is the high degree of risk and uncertainty associated with them (Bacon, 1992; Gunasekarana et al., 2001; Irani et al., 2002; Wu and Ong, 2008). IS/IT projects involve technological as well as organizational uncertainties (Wu and Ong, 2008). Technological uncertainty originates from rapid change in such technologies; therefore, investments might become obsolete quickly. Organizational uncertainty ranges from unpredictable user resistance, the cost of employee burnout, and the maintenance expenses (Wu and Ong, 2008). Interdependencies also exist among the projects because they normally support common objectives (Eilat et al., 2006), use shared input and often impact each other's output. The complexity of IS/IT projects as well as their interdependencies poses a challenge when applying methods for the prioritization of these investments (Bardhan et al., 2004). That is why researchers have criticized conventional methods for evaluating IS/IT investments (e.g. Farbey et al., 1993). This study focuses on IS/IT projects because these projects typically demonstrate both interdependency and project uncertainty.

This paper is organized as follows. In Section 2 we present a brief literature review on project portfolio selection. We then describe the proposed methodology in Section 3. In Section 4 we illustrate the proposed methodology using a numerical example. In Section 5 we present our concluding remarks and in Section 6 we discuss our research limitations and future research directions.

2. Research background

In this section we first review the literature on portfolio selection and then describe DEA and FDEA.

2.1. Portfolio selection

Achieving maximal project portfolio value for the resources used is often complicated by multiple selection criteria, subjective and imprecise assessments and project interdependencies (Ravanshadnia et al., 2010, 2011). Danila (1989) defines portfolio selection as selecting an investment from a list of candidate investments in order to maximize some objectives without violating constraints. Cooper et al. (1997) categorize portfolio selection problems into two categories: dynamic and static. Bard et al. (1988) suggest that in the dynamic approach, we face projects that are in progress (active projects) and those that have not started yet (candidate projects). Static portfolio selection involves evaluating portfolios of candidate projects. An example situation might be an organization that has limited funds to allocate for new investments. The focus of this paper is on the static portfolio selection problem (Basso and Peccati, 2001).

Different methods have been proposed to select optimum portfolios of projects. For example, Cooper et al. (1997) used a decision tree and proposed a model which incorporated probabilities of success. Similarly, a scoring method was proposed by Henriksen and Traynor (1999) who calculated a relative value for each project based on project merit as well as cost. Wang and Hwang (2007) presented a methodology for selecting fuzzy portfolios of R&D projects based on an optimized value and strategic balance. Coffin and Taylor (1996) proposed a multiple-criteria decision-making (MCDM) methodology for selecting and scheduling R&D investments using fuzzy logic and a standard beam search. Table 1 summarizes a list of publications in the literature that deal with portfolio selection and lists their strengths and weaknesses.

A number of researchers have focused on project uncertainty when selecting portfolios of projects (e.g. Chen and Cheng, 2009; Huang et al., 2008; Lin and Hsieh, 2004; Tiryaki and Ahlatcioglu, 2005, 2009). Huang et al. (2008), for instance, used a fuzzy analytic hierarchy process (AHP) for R&D portfolio selection which considered project uncertainty. Tiryaki and Ahlatcioglu (2009) used fuzzy-AHP for selecting portfolios of stocks in the stock exchange market. Chen and Cheng (2009) employed a methodology based on the fuzzy MCDM and ranked portfolios of IS projects under uncertainty conditions. However, none of these studies adequately treated 'project interdependencies' which has been long known as an important drawback for the existing portfolio selection methodologies (Baker and Freeland, 1975). On the other hand, a number of researchers have taken project interdependencies into consideration when developing portfolio selection methodologies (e.g. Bardhan et al., 2004; Dickinson et al., 2001; Eilat et al., 2006; Schmidt, 1993; Verma and Sinha, 2002). Eilat et al. (2006), for example, proposed a DEA based methodology for R&D portfolio selection which considered interactions among projects. Additionally, Bardhan et al. (2004) used nested real options and traditional discounted cash flow to evaluate interrelated portfolios of IT investments. However, none of these studies have considered project uncertainty.

2.2. DEA model

DEA is a widely used mathematical programming approach for comparing the inputs and outputs of a set of homogenous Decision Making Units (DMUs) by evaluating their relative efficiency. A DMU is considered efficient when no other DMU can produce more outputs using an equal or lesser amount of inputs. The DEA generalizes the usual efficiency measurement from a single-input single-output ratio to a multiple-input multiple-output ratio by using a ratio of the weighted sum of outputs to the weighted sum of inputs.

Formulation (1) presents the basic DEA model (in its ratio form) called the Charnes, Cooper and Rhodes (CCR) model introduced by Charnes et al. (1978). The objective of Formulation

Table 1
A summary of the portfolio selection models in the literature.

Author and research aim	Strength	Weakness
Bardhan et al. (2004) introduced a nested real options and traditional discounted cash flow for IT investments	They claim that "Our nested options model provides a better understanding of project interdependencies on valuation and prioritization decisions [p. 33]"	They assume that "the overall portfolio volatility can be estimated accurately [p. 53]"
Lin and Hsieh (2004) introduced a fuzzy weighted average; Fuzzy integer linear programming for projects in food industry	Their method copes with incomplete information and uncertain circumstances	They assume that "all strategic plans are independent of one another [p. 389]"
Eilat et al. (2006) introduced a methodology based on DEA and balanced scorecard for R&D projects	They consider interactions among projects	They do not consider uncertainty conditions in their methodology
Huang et al. (2008) introduced a fuzzy AHP for R&D projects	They extend "fuzzy AHP application for R&D project selection in the public sector [p.1050]"	They assume the evaluation criteria are independent
Tiryaki and Ahlatcioglu (2009) introduced a fuzzy AHP for stock selection	They rank "a set of stocks in a fuzzy environment [p. 67]"	They do not consider the interdependencies among the DMUs
Tiryaki and Ahlatcioglu (2005) introduced a fuzzy MCDM for stock selection	Their model "demonstrates the usefulness of fuzzy methodology in financial problems [p. 144]"	They do not consider the interdependencies among the DMUs
Chen and Cheng (2009) introduced a fuzzy MCDM for IS projects	Their model "provides more flexible and objective information in dealing with multicriteria decision-making problems in a fuzzy environment [p. 398]"	They do not consider the interdependencies among the IS projects

(1) is to maximize the efficiency of each DMU (i.e. its weighted sum of outputs divided by its weighted sum of inputs). The constraints of Formulation (1) assume that the efficiency values of all the DMUs, computed by the weights system for the DMU under examination, are lower than one. The number of DMUs, the number of input criteria, and the number of output criteria are represented by n, m, and s; respectively. $x_{ij}(1,\ldots,m)$ and $y_{rj}(r=1,\ldots,s)$ are respectively the values for the ith input and the rth output of the jth project ($j=1,\ldots,n$). Each DMU's relative efficiency is calculated by dividing the weighted sum of outputs by the weighted sum of inputs. In Formulation (1), the weights u and v, variables of the DEA model, are computed in a manner that allows each DMU to show itself at its optimal efficiency. The constant ε is a positive infinitesimal number that operates as a lower bound for u and v.

$$\begin{aligned} &\text{Max}\, \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}} \\ &s.t.\, \frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \le 1 \quad \forall j \\ &u_r \ge \varepsilon, \\ &v_i \ge \varepsilon. \end{aligned} \tag{1}$$

The efficiency value of each DMU is calculated by running Formulation (1) n times (each time assessing a different DMU and calculating the maximum possible efficiency of that particular DMU under the condition that no DMU's efficiency is higher than 1). If a DMU is given an efficiency score of 1, it is considered to be efficient; an efficiency score less than 1 indicates inefficiency. The nomenclature below lists the variables used in this paper and provides a brief description for each variable.

Nomenclature

- m the number of inputs for a project or portfolio
- s the number of outputs for a project or portfolio
- n the total number of projects
- z_k the particular selection of projects in portfolio k($z_{jk}=1$, if project j participates in portfolio k; otherwise $z_{jk}=0$)
- x_{ij} the amount of input i required by project j
- y_{rj} the amount of output r produced by project j
- $\hat{x}_{ik}$ the amount of input i allocated to portfolio k
- $\hat{y}_{rk}$ the amount of output r produced by portfolio k
- U^i the resource interaction matrix for input i
- u^i_{jk} the interaction between project j and project k for input i
- V^r_{jk} the interaction between projects j and k for output r
- P_{jk} the marginal change in the success likelihood of project j when project k is participating in a portfolio comprised of project j
- α a parameter between 0 and 1. Linear programming problems would be solved for each given α-cut
- λ_j the weights used as variables in the FDEA model to derive the best efficiency of the DMUs
- u and v the weights used as variables in the DEA model to derive the best efficiency of the DMUs
- ε a positive infinitesimal number used as a lower bound for u and v
- $\tilde{x}_{ij} = \left(x^b_{ij}, x^c_{ij}, x^d_{ij}\right)$ the ith input vector for the jth DMU in the FDEA model
- $\tilde{y}_{rj} = \left(y^b_{rj}, y^c_{rj}, y^d_{rj}\right)$ the rth output vector for the jth DMU in the FDEA model
- $x^b_{ij}(x^d_{ij})$ the left (right) bound of the fuzzy variable $\tilde{x}_{ij}$
- $y^b_{rj}(y^d_{rj})$ the left (right) bound of the fuzzy variable $\tilde{y}_{rj}$
- $x^c_{ij}(y^c_{rj})$ the core of the fuzzy variable $\tilde{x}_{ij}\left(\tilde{y}_{rj}\right)$
- $\tilde{x}_{iq} = \left(x^b_{iq}, x^c_{iq}, x^d_{iq}\right)$ the ith input vector for the qth DMU in the FDEA model
- $\tilde{y}_{rq} = \left(y^b_{rq}, y^c_{rq}, y^d_{rq}\right)$ the rth output vector for the qth DMU in the FDEA model
- $x^b_{iq}(x^d_{iq})$ left (right) bound of the fuzzy variable $\tilde{x}_{iq}$
- $y^b_{rq}(y^d_{rq})$ left (right) bound of the fuzzy variable $\tilde{y}_{rq}$
- $x^c_{iq}(y^c_{rq})$ the core of the fuzzy variable $\tilde{x}_{iq}\left(\tilde{y}_{rq}\right)$

2.3. FDEA model

A fuzzy variable is a variable with an imprecise value, as opposed to a variable with an exact (i.e., crisp) value. Each fuzzy variable can be considered as a function that its domain is a specified set. Each numerical value in the domain has a specific "membership function" in which the minimum and the maximum feasible grades are 0 and 1, respectively. Fuzzy variables are said to represent the physical world more realistically than crisp (single-valued) numbers. The following example demonstrates the concept of a fuzzy variable: the fuzzy variable temperature might have the primary term set {cold, warm, hot}, where each primary term represents a specific fuzzy set. Fig. 1 illustrates the primary term values of the fuzzy variable temperature. In this example, temperature at −5 has membership in sets "warm" and "cold".

The triangular fuzzy variable is the most popular kind of fuzzy variable. As shown in Fig. 2, a triangular fuzzy variable is a fuzzy variable represented with three points (b,c,d). A triangular fuzzy variable $\tilde{x}$ in R, denoted by (b,c,d), is a triangular fuzzy variable if its membership function $\mu_{\tilde{x}}: R \rightarrow [0,1]$ satisfies: $\mu_{\tilde{x}}(z) = \begin{cases} (z-b)/(c-b), b \le z \le c \\ (d-z)/(d-c), c \le z \le d \\ 0, otherwise \end{cases}$. c is called the core of the triangular fuzzy variable $\tilde{x}$; b and d are the left and right bounds of $\tilde{x}$, respectively.

A fuzzy variable, represented by a membership function such as the one above, can be seen as a set of nested intervals, each associated with a membership level α. This parameter, in the context of decision making, can be seen as a measure of the risk of accepting an α-cut. This risk level is defined in the interval [0,1]. The membership grade of the fuzzy triangular variable $\tilde{x}$ depicted in Fig. 2 for point c is $\mu_{\tilde{x}}(c) = 1$. This indicates that c is the most credible value of $\tilde{x}$ and is associated with the cut α = 1. For the boundary points b and d, the membership grade is zero ($\mu_{\tilde{x}}(b) = 0$ and $\mu_{\tilde{x}}(d) = 0$) and the interval [b, d] is associated with the cut α = 0. The boundary points of the triangular fuzzy variable $\tilde{x}$ can be interpreted as the most risky values since their grade of "belonging" is zero. Generally, with growth of the membership grade $\mu_{\tilde{x}}(z)$, credibility increases and risk decreases. Fig. 3 illustrates a possible fuzzy representation of "more or less 0.5". As shown, the level α = 0.5 corresponds to the interval [0.35, 0.65], whereas for a higher α-cut such as α = 0.6, the interval [0.4, 0.6] might be selected as a substitute of "more or less 0.5" in order to increase the credibility of the statement. On the contrary, the uncertainty

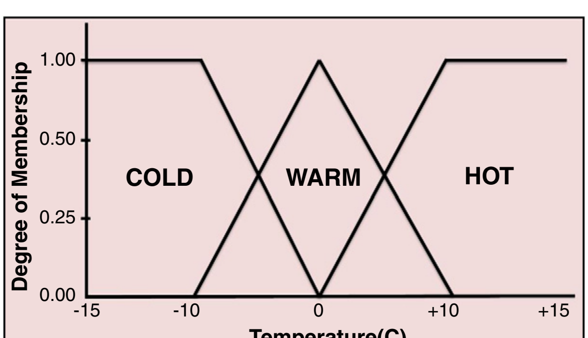

Fig. 1. The fuzzy variable temperature.

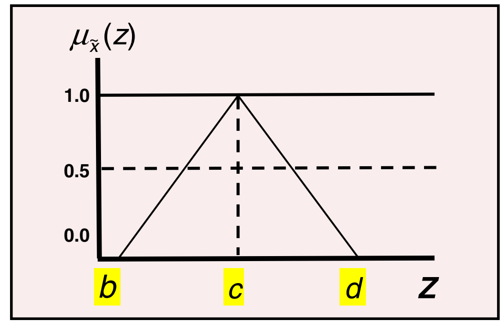

Fig. 2. The triangular fuzzy variable $\tilde{x} = (b,c,d)$.

or risk increases as the lower α increases. For example, for α = 0.25 the broader interval [0.25, 0.75] will be used to represent "more or less 0.5". Obviously, the maximum level of statement credibility (i.e. α = 1) corresponds to the crisp number 0.5 as a surrogate of the fuzzy statement "more or less 0.5".

FDEA is a method for measuring and comparing the attractiveness of a set of alternatives under condition of uncertainty (Lertworasirikul et al., 2003). Saati et al. (2002) proposed a DEA model which uses fuzzy data (see Formulation (2)[1]). This model has been used for finding the optimal solution among proposed alternatives (Azadeh et al., 2007; Guo and Tanaka, 2008; Saati and Memariani, 2005, and Wu et al., 2005). Azadeh et al. (2007), for example, used an integrated model of FDEA and computer simulation for finding optimal alternatives. Saati et al.'s (2002) proposed method converts a fuzzy problem into a linear programming model based on the α-cut. Here, an α-cut yields a subset of values of the fuzzy variable $\tilde{y}$ that have membership values ≥ α. The α-cut technique is an approach to convert a fuzzy model to an easily solvable crisp linear model.

In accordance with the recommendation of Saati et al. (2002), this paper uses α = 0.5; however, sensitivity of the result for different values of α is investigated in Appendix 1.

$$\begin{aligned} &Min \quad Z = 0 \\ &s.t.\ \theta\left(\alpha x_{iq}^{c} + (1-\alpha)x_{iq}^{b}\right) \ge \sum_{j=1}^{n} \lambda_j \left(\alpha x_{ij}^{c} + (1-\alpha)x_{ij}^{d}\right) \qquad \forall i, \\ &\alpha y_{rq}^{c} + (1-\alpha)y_{rq}^{d} \le \sum_{j=1}^{n} \lambda_j \left(\alpha y_{rj}^{c} + (1-\alpha)y_{rj}^{b}\right) \qquad \forall r, \\ &\lambda_j \ge 0 \qquad \forall j. \end{aligned} \tag{2}$$

Formulation (2) converts the fuzzy linear programming problem to a crisp parametric linear programming problem. $\tilde{x}_{ij} = \left(x_{ij}^{b}, x_{ij}^{c}, x_{ij}^{d}\right)$ and $\tilde{y}_{rj} = \left(y_{rj}^{b}, y_{rj}^{c}, y_{rj}^{d}\right)$ are the ith input and the rth output for the jth DMU and α is a parameter between 0 and 1. The weights λ_j, the variables of the FDEA analysis, are calculated so that each DMU operates at the maximum efficiency. By running Formulation (2) n times (each time assessing a different DMU), the efficiency value of each DMU is calculated. In the α-level based approach, Lertworasirikul (2002) used the

[1] A complete explanation of how Saati et al. (2002) derived Eq. (2) from Eq. (1) is available at: http://ghapanchi.web.officelive.com/Documents/FDEA%20description.pdf.

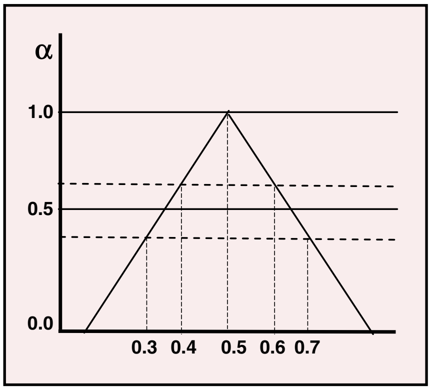

Fig. 3. The fuzzy variables "more or less than 0.5" for α = 0.5.

following four methods to solve an interval-valued linear programming problem based on the DMs' optimistic or pessimistic preferences: Best–Best, Worst–Worst, Best–Worst, and Worst–Best. In Formulation (2), the Best–Best method is used where every DMU is considered in an optimistic way. From the input and output intervals at each α-level, the smallest inputs and the larger outputs for each DMU are compared to the inner part of the efficiency frontier.

3. The proposed methodology

The methodology suggested by this paper comprises the following four steps:

Step 1 Modeling the problem;
Step 2 Selecting candidate projects;
Step 3 Portfolio generation and establishing maximal portfolios; and
Step 4 Evaluation of maximal portfolios.

Our proposed methodology (See Fig. 4) begins with "Modeling of the problem" in terms of establishing evaluation criteria (input and output criteria for FDEA) as well as providing fuzzy estimates of input, output and associated risk for each project (Step 1). Individual projects are then assessed using FDEA followed by screening inefficient and high risk projects (Step 2). A branching procedure is then used to generate portfolios of the remaining projects (Step 3). Portfolios are subsequently evaluated using FDEA (Step 4). The following explains each step in detail.

3.1. Step 1: modeling the problem

In this paper, portfolios of IS/IT projects are regarded as DMUs. To begin with, input and output indices are established. Next, input, outputs and associated risk for each project as well as the interactions (including input, output, and possibility interactions) between projects are estimated. For qualitative criteria, linguistic values that are stated as triangular fuzzy variables are used. In this study, we use the linguistic values and their equivalent triangular fuzzy variables in [0,1] as suggested by Fu (2008, p.146).

As shown in Table 2, the scale of uncertain linguistic assessments of the DMs with regards to the chances of the projects being successful is shown in the left column. Each linguistic expression on this scale can be described mathematically using triangular fuzzy variables. As stated earlier, a useful representation for triangular fuzzy variables is through triple numbers as shown in the right column of Table 2. For example, the linguistic variable 'Very low' is expressed by the points 0, 0.15 and 0.3. It means that a 'Very low' subjective probability of the project success is associated with the fuzzy variable 'about 0.15', with boundary points 0 and 0.3. In other words, the chances for projects' success are between 0 and 0.3 and the truth of the statement grows linearly with the chance approaching 0.15. The membership grade, or the truth of the statement 'Very low' is maximal ($\mu_{VeryLow}(0.15) = 1$) at .15, and it is minimal at 0 and 0.3 ($\mu_{VeryLow}(0) = 0, \mu_{VeryLow}(0.3) = 0$). We should note that the scale used by Fu (2008) is applicable for criteria requiring minimization, as he calls them "cost criteria". On the contrary, in our study, the scale in Table 2 is reversed to represent the chance of a project being successful (maximization criterion).

3.2. Step 2: selecting candidate projects

To select candidate projects, we suggest calculating two indices for each project: efficiency (the efficiency score calculated by the FDEA model), and average risk (calculated by multiplying the average input of the project by its likelihood of failure). Each project is screened using a minimal threshold for the efficiency index and maximal thresholds for the risk. Such thresholds also assist in reducing the number of candidate projects and the number of alternative portfolios.

3.3. Step 3: portfolio generation and establishing maximal portfolios

In this step we generate all possible portfolios for subsequent assessment. Herein, the branching procedure proposed by Eilat et al. (2006) is used to generate the alternative portfolios. Assuming that we have n projects, we start with an empty portfolio (node 0). From node 0, we branch to n nodes ($i = 1,\ldots, n$) by adding a single project to the portfolio each time according to the order of their indices. Subsequently, this process is repeated for each node formed in the previous stage. According to this branching scheme, if a branch results in a portfolio which exceeds the available resource(s) then its descendants are not generated. In addition, if two nodes present an identical portfolio, we only consider one of them. We continue this process until all possible portfolios are formed.

As mentioned previously, the current study takes project interactions into account. This paper categorizes the interactions into three classes: input interactions, output interactions, and possibility interactions: (1) input interaction is present when the amount of a resource required by project x depends on whether or not project y is included in the portfolio that contains project x; (2) output interaction is present when the amount of an output produced by project x depends on whether

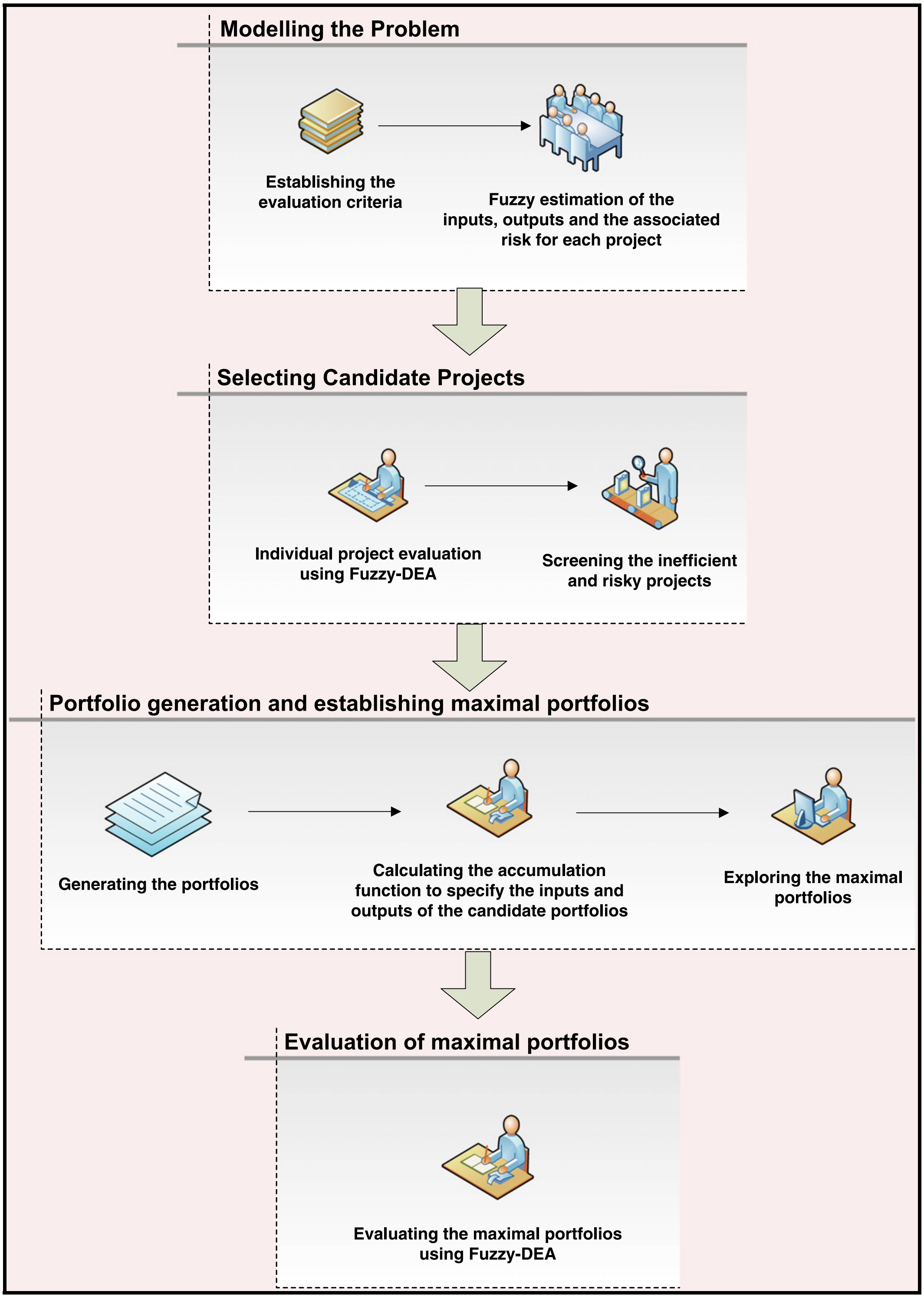

Fig. 4. The proposed methodology.

or not project y is included in the portfolio that contains project x; and (3) possibility interaction is present when the likelihood of success for project x depends on whether or not project y is included in the portfolio that contains project x. For example, let's assume that cost is an input criterion and that we have two projects of x and y which would cost us \$300,000 and \$200,000 respectively. An input interaction of \$ −50,000 between projects x and y means that by including both projects in the same portfolio we could save \$50,000 overall and pay \$450,000 rather than \$500,000.

After all possible portfolios are created, it is necessary to accumulate the inputs and outputs of the projects which make up a particular portfolio. However, since this paper takes interactions between projects into consideration, accumulated inputs

Table 2
The linguistic variables and their associated triangular fuzzy variables used to evaluate the qualitative criteria.

Linguistic variables	Fuzzy variables
Extremely low	(0,0,0.05)
Very low	(0,0.15,0.3)
Low	(0.15,0.3,0.45)
Medium	(0.35,0.5,0.65)
High	(0.55,0.7,0.85)
Very high	(0.7,0.85,1)
Extremely high	(0.95,1,1)

and outputs of a portfolio cannot be computed by simply adding up the inputs and outputs of the projects participating in that portfolio. Thus, we customized the equations proposed by Eilat et al. (2006) to calculate the interaction between projects in terms of the input and output for fuzzy portfolios (See Eqs. 3 and 4). Eqs. (3) and (4) specify a general accumulation function for all combined input, output and possibility interactions. These accumulation functions include combined effect of input, output and possibility interactions and are applied to the inputs and outputs of the projects in each portfolio to compute aggregate inputs and outputs of the portfolio.

The input accumulation function, Eq. (3), calculates the input of each portfolio where $\tilde{x}$ represents the fuzzy input value of each project. The output accumulation function, Eq. (4), computes the output of each portfolio where $\tilde{y}$ represents the fuzzy output value of each project and $\tilde{p}$ represents the fuzzy probability value of each project. After the possible portfolios are generated using a branching procedure, Eqs. (3) and (4) are applied to all the portfolios in order to calculate the overall input and output of each feasible portfolio.

The amount of a particular input demanded by a given portfolio can be calculated by summing the individual projects' inputs plus the difference in the portfolio input accumulation that stems from the input interaction between the projects within that particular portfolio, as presented in Eq. (3). $\tilde{p}_{jk}$ shows the marginal likelihood of the success of project j when project k is participating in a portfolio comprising project j. Similar to Eq. (3), Eq. (4) provides the accumulation for output for each portfolio. The only difference is that here the possibility interactions between the projects within a particular portfolio should be taken into account. $\left[\tilde{y}_{rj}+\sum_{i=1}^{j-1}\tilde{v}_{ji}\cdot\left(\sum_{j=1}^{n}\tilde{p}_{ji}z_{ik}\right)\cdot z_{ik}\right]$ represents the sum of each individual project output r plus the difference in the accumulation of output r that stems from the output interaction between the projects; it is then multiplied by $z_{jk}\left(\sum_{j=1}^{n}\tilde{p}_{ji}z_{ik}\right)$ in order to take only the projects which are present in a certain portfolio into account. Finally by adding all these values, $\hat{y}_{rk}$represents amount of output r returned by portfolio k, as presented in Eq. (4).

$$\hat{x}_{ik}=\sum_{j=1}^{n}\tilde{x}_{ij}z_{jk}+U^{i}z_{k},\qquad \forall i,k. \tag{3}$$

$$\hat{y}_{rk}=\sum_{j=1}^{n}z_{jk}\left(\sum_{j=1}^{n}\tilde{p}_{ji}z_{ik}\right)\left[\tilde{y}_{rj}+\sum_{i=1}^{j-1}\tilde{v}_{ji}.\left(\sum_{j=1}^{n}\tilde{p}_{ji}z_{ik}\right).z_{ik}\right]. \tag{4}$$

After calculating the values of the input and outputs for each generated portfolio using the accumulation function, we establish maximal portfolios. A portfolio is said to be maximal if the following two conditions are met (Eilat et al., 2006):

- The portfolio is feasible or the amount of input i required for the portfolio is equal to or less than the total amount of that particular input $\forall i$.
- Adding any new project to the portfolio would breach the input constraints.

3.4. Step 4: evaluation of maximal portfolios

Portfolios can be modeled as DMUs with specific inputs and outputs. After establishing the maximal portfolios, FDEA is applied once more, this time at the portfolio level, to determine the efficiency score for each maximal portfolio. Portfolio calculations can be performed using different values for α to show the sensitivity of the result and help decision-makers in making their final choice of portfolio.

4. Numerical example

Like most of the-state-of-the-art papers on portfolio selection methodologies (Bardhan et al., 2004; Chen and Cheng, 2009; Eilat et al., 2006; Tiryaki and Ahlatcioglu, 2005; Tiryaki and Ahlatcioglu, 2009), this study uses a numerical example to illustrate an application of the proposed methodology. The example relates to a decision making problem in a national governmental organization. This organization has a hierarchical structure composed of several divisions. One of the divisions is in charge of designing, selecting and outsourcing developmental projects. This particular division is considering a list of 16 IS/IT projects. The projects have interdependencies in terms of resources, results, and the probability of success. On the other hand, like a typical IS/IT project, the projects involve conditions of uncertainty. There is $600 million available for the fulfillment of these projects and this budget is insufficient to proceed with all 16 projects.[2] The decision model should assist with choosing the most efficient portfolio of the projects subject to the monetary limitation. The proposed methodology is illustrated through the following example.

4.1. Step 1: modeling the problem

In step 1 of the proposed methodology, input and output indices are established. First, one input indicator and three output indicators were determined using the strategic plan. The only input indicator selected was cost of the project in millions of

[2] The data in this example is changed to avoid any confidentiality issues.

dollars (x_{1j}). The output indicators include: the number of potential subsequent investments (y_{1j}), contribution to the work-flow improvement (y_{2j}), and percentage of contribution to electronic readiness (y_{3j}). A probability of success P_j is also associated with each project. Regarding the first output criterion, the managers of the organization under study who were involved in developing their strategic plan preferred "the number of potential subsequent investments" over "the total value of potential subsequent investments" because there was no significant difference between the values of the available subsequent investments. With respect to the second output criterion, contribution to the work-flow improvement, a Likert scale (Likert, 1932) was used. Likert scale is a psychometric scale which is commonly used in questionnaires. A Likert questionnaire item enables respondents to specify their level of agreement with predefined answers (Likert, 1932). For our second output criterion, a seven-point Likert scale was used (1 = 'extremely low', 2 = 'very low', 3 = 'low', 4 = 'medium', 5 = 'high', 6 = 'very high', 7 = 'extremely high'), and respondents were asked to pick one of these predefined options as their answer to the question posed on the second output criterion (the extent to which running a given project may contribute to the improvement of the work-flow of the government). For the second output criterion, y_{2j}, linguistic values introduced in Table 2 were used. Table 3 shows input and output indices of our decision making problem. It should be noted that these input and output indices are specific to the context of the example used in this study and are directly extracted from the strategic plan of the organization under study. Thus, one requirement of this methodology is the development of input and output criteria for any potential application.

After establishing the decision criteria, fuzzy values for the input and output indicators as well as associated risk were estimated for each project. To do so, a group of 15 experts were invited and provided with a detailed description of each project, requirements of each project, and information about units of costs, man-hours, etc. Afterwards, the respondents received a questionnaire to enter their estimates. The raw score for the input, the outputs, the associated risk for each project, and the interactions (including input, output, and possibility interactions) among each pair of two projects were estimated by the experts in a fuzzy manner. Subsequently, for each project, a symmetric triangular fuzzy variable was computed for each input, output, and success probability criterion by averaging the values estimated by the experts.

"Response stability" measures the stability across time by testing whether or not respondents give the same answers to the same questions over a period of time (Neuman, 2006). In this research, we used the test–retest method which has been proposed as an efficient method for assessing the response stability of respondents over a period of time (Neuman, 2006). We asked the same questions from the same respondents twice within a nine month interval and computed the Pearson correlation coefficients for the responses. The Pearson correlation coefficients for all the questions were greater than 0.7 indicating a high response stability of the questions.

The interactions among the input, outputs and probability of success are included in the interaction matrices. U represents the input interaction matrix; (V^1, V^2, and V^3) represent the outputs interaction matrices, and P shows the probability interaction matrix (See Table 4). For each project, the average for input, outputs, and success likelihood as well as its interactions with other projects are listed in Table 4. In this table, u^i_{jk} represents the value interaction between project j and project k for input i, $V^r{}_{jk}$ shows the value interaction between project j and project k for output r, and P_{jk} represents the marginal change in the success likelihood of project j when project k is participating in a portfolio comprising project j. The project interactions are applicable after the portfolios are created in Step 3.

An example of the cost of project interaction would be the selection of both projects 7 and 8 which have some shared activities. Since they share some resources, the total cost of the two projects would decrease by at least \$12.6 million and at most \$14 million. An example of *potential subsequent projects* interaction would be including projects 3 and 4 in the same portfolio. Because there is a future project for which both are prerequisites, the sum of these two projects' number of potential subsequent projects would increase by 1. Work-flow improvement interaction is seen if projects 7 and 8 that have synergy were simultaneously selected, since they would then have a stronger effect and their accumulation improvement level would increase by 0.15 on average. With respect to e-readiness, if projects 4 and 5 that have synergy in benefits are selected in a portfolio, they have stronger impact, and their accumulation function on human resource e-readiness would increase by at least 7.1%, at most 10.3%, and by 8.7% on average.

Table 3
The decision making criteria used in the numerical example.

Data type	Criterion	Explanation
Input	Cost	The project cost
Output	Potential subsequent projects	The number of projects which their adoption is contingent to this project's implementation
	Work-flow improvement	The degree of government work-flow improvement based on a seven-point Likert scale (in addition to the reduction in resources and employees, and citizens' satisfaction)
	E-readiness contribution margin	The likeliness of citizens, businesses, government managers, employees, and other stakeholders increasing their participation in the IS/IT activities as a result of this project's implementation

4.2. Step 2: selecting candidate projects

In order to have a manageable number of projects for the purpose of constructing and evaluating all possible portfolios of projects, we performed an initial screening on each individual project and weeded out projects with considerably low efficiency. To do so, we calculated two indices for each project: (i) the FDEA efficiency value for the project; and (ii) its average risk, calculated by multiplying the average input of the project by its probability of failure. The data in Table 4 was used to calculate the FDEA score for each individual project. The results are depicted in Table 5. Subsequently, through a minimal threshold for the

Table 4
The project data.

Project	Input ($ million)	Outputs			Probability of success
		1	2	3	
1	(412,435,458)	(128,132,136)	(0.73,0.865,0.95)	(42,46,50)	(0.412,0.442,0.472)
2	(174,178,182)	(69,75,81)	(0.05,0.16,0.29)	(6,9,12)	(0.745,0.754,0.763)
3	(225,242,259)	(27,28,29)	(0.68,0.74,0.91)	(36,41,46)	(0.605,0.66,0.715)
4	(308,323,338)	(85,90,95)	(0.55,0.7,0.85)	(87,90,93)	(0.396,0.441,0.486)
5	(175,189,203)	(73,75,77)	(0.37,0.55,0.68)	(71,75,79)	(0.545,0.565,0.585)
6	(84,93,102)	(66,70,74)	(0.07,0.17,0.31)	(45,47,49)	(0.346,0.355,0.364)
7	(349,370,391)	(123,130,137)	(0.95,0.99,0.99)	(39,44,49)	(0.213,0.261,0.309)
8	(245,271,297)	(41,43,45)	(0.31,0.45,0.59)	(32,37,42)	(0.225,0.255,0.285)
9	(151,154,157)	(58,60,62)	(0.35,0.45,0.65)	(25,27,29)	(0.612,0.687,0.762)
10	(265,281,297)	(49,52,55)	(0.68,0.79,0.94)	(37,41,45)	(0.541,0.572,0.603)
11	(345,362,379)	(21,24,27)	(0.15,0.18,0.21)	(54,58,62)	(0.211,0.231,0.251)
12	(215,222,229)	(4,6,8)	(0.19,0.2,0.21)	(56,59,62)	(0.04,0.05,0.06)
13	(385,391,397)	(6,8,10)	(0.33,0.34,0.35)	(34,36,38)	(0.235,0.25,0.265)
14	(454,474,494)	(7,9,11)	(0.44,0.47,0.5)	(11,13,15)	(0.304,0.324,0.344)
15	(384,390,396)	(7,8,9)	(0.2,0.22,0.24)	(48,51,54)	(0.245,0.265,0.285)
16	(384,391,398)	(9,11,13)	(0.16,0.18,0.2)	(52,54,56)	(0.25,0.275,0.3)
$U_{1,10} = (-32, -28, 4, -24.8)$		$V^1_{1,10} = (3.75, 4.25, 4.5)$		$P_{2,7} = (0.108, 0.111, 0.114)$	
$U_{2,7} = (-14.4, -12.5, -10.6)$		$V^1_{3,4} = (1, 1, 1)$		$P_{7,6} = (0.148, 0.167, 0.186)$	
$U_{4,5} = (-24, -21, -18)$		$V^1_{5,6} = (1, 2, 3)$		$P_{7,8} = (0.187, 0.194, 0.201)$	
$U_{6,7} = (-19, -16.8, -14.6)$		$V^1_{7,8} = (2, 2, 2)$		$P_{8,6} = (0.0064, 0.071, 0.078)$	
$U_{6,8} = (-5, -4.2, -3.6)$		$V^2_{1,3} = (0.3, 0.44, 0.58)$			
$U_{7,8} = (-14, -13.3, -12.6)$		$V^2_{7,8} = (0.05, 0.15, 0.3)$			
$U_{9,10} = (-19, -17.4, -15.8)$		$V^2_{7,10} = (0.07, 0.15, 0.27)$			
		$V^3_{4,5} = (7.1, 8.7, 10.3)$			
		$V^3_{4,6} = (9.7, 10.6, 11.5)$			
		$V^3_{5,6} = (12.5, 13.7, 14.9)$			
		$V^3_{5,9} = (4.8, 13.7, 14.9)$			
		$V^3_{7,8} = (7.8, 8.9, 10)$			

efficiency index (0.7) and maximal thresholds for the risk index ($200 million), we weeded out a number of projects that had an inferior amount of efficiency. Projects 11 through 16 were screened out since they either had efficiency less than 0.7 or average risk greater than $200 million.

Table 5
The sorted individual portfolio evaluation results for $\alpha = 0.5$.

Project	Efficiency	Average risk ($ million)
6	1.48	59.98
5	1.36	82.21
9	1.35	48.2
3	1.24	82.28
10	1.14	120.26
7	1.05	273.43
4	0.98	180.55
1	0.83	242.73
2	0.75	43.78
8	0.75	201.89
12	0.62	210.9
11	0.37	278.37
14	0.36	320.424
13	0.34	293.25
15	0.32	286.65
16	0.31	283.47

4.3. Step 3: portfolio generation and establishing maximal portfolios

Next, a branching procedure was applied to the selected projects (projects 1 through 10). The total number of possible portfolios was 2^nor 1024. In order to calculate the total amount of input i required for a given portfolio and the total amount of output j produced by that portfolio, the accumulation function was applied. Eqs. (3) and (4) were applied to compute the accumulated inputs and outputs, with consideration of the interactions between projects. Out of the 1024 possible portfolios, 36 portfolios met both conditions for maximal projects. The number of projects in each of the 36 maximal portfolios ranged from 1 to 4.

4.4. Step 4: evaluation of maximal portfolios

FDEA was applied once more, this time to assess the maximal portfolios. Table 6 demonstrates the ranked portfolios. For each portfolio, Table 6 provides a 10-digit binary vector (as identifier), its accumulated input and outputs, and the efficiency. For instance, the first portfolio contains projects 3, 5, and 9, and has the highest efficiency among all 1024 portfolios (assuming $\alpha = 0.5$). The evaluations can be also done as per other values of α (sensitivity analysis).

Table 6
The sorted portfolio evaluation results for α = 0.5.

Rank	Portfolio number	Label	Input	Output			Efficiency
				1	2	3	
1	388	A0010100010	(551,585,619)	(92,102,113)	(0.83,1.11,1.54)	(81,93,107)	1.45
2	418	A0010010010	(460,489,518)	(75,85,95)	(0.65,0.86,1.26)	(53,62,73)	1.38
3	308	A0100110010	(584,614,644)	(151,167,184)	(0.48,0.8,1.23)	(91,103,116)	1.35
4	164	A0000100011	(572,607,641)	(102,113,125)	(0.78,1.07,1.46)	(79,90,101)	1.33
5	37	A0010110000	(484,524,564)	(80,88,96)	(0.64,0.86,1.16)	(89,100,112)	1.33
6	148	A0110000010	(550,574,598)	(103,116,130)	(0.66,0.92,1.37)	(42,52,64)	1.3
7	261	A0001110000	(543,584,625)	(97,109,121)	(0.44,0.68,0.92)	(118,132,146)	1.27
8	21	A0000010011	(481,511,540)	(85,96,107)	(0.61,0.82,1.17)	(51,59,67)	1.26
9	194	A0100000011	(571,596,620)	(113,128,142)	(0.62,0.88,1.28)	(40,49,58)	1.26
10	178	A0010010001	(574,616,658)	(66,73,81)	(0.8,1,1.33)	(57,67,78)	1.21
11	402	A0110100000	(574,609,644)	(108,117,128)	(0.65,0.92,1.27)	(65,76,88)	1.2
12	51	A0000110001	(524,563,602)	(90,99,108)	(0.59,0.82,1.08)	(87,96,106)	1.18
13	114	A0000011010	(565,600,635)	(103,122,142)	(0.58,0.79,1.1)	(45,54,64)	1.16
14	28	A0110010000	(483,513,543)	(91,100,109)	(0.47,0.67,0.98)	(42,51,60)	1.14
15	58	A0100011000	(574,612,650)	(126,145,166)	(0.41,0.62,0.86)	(35,43,53)	1.11
16	84	A0000111000	(589,635,681)	(108,125,143)	(0.57,0.79,1)	(81,92,103)	1.08
17	147	A0001010010	(543,570,597)	(92,106,120)	(0.46,0.68,1.02)	(75,86,97)	1.08
18	516	A0100010001	(523,552,581)	(101,111,122)	(0.43,0.63,0.9)	(40,47,54)	1.06
19	282	A0011000000	(533,565,597)	(51,59,68)	(0.63,0.8,1.06)	(56,67,78)	1.05
20	770	A0000100110	(571,614,657)	(85,95,105)	(0.49,0.73,1.06)	(66,76,86)	0.983
21	275	A1000000010	(563,589,615)	(88,100,111)	(0.51,0.69,0.94)	(33,39,46)	0.983
22	54	A0000110100	(499,549,598)	(75,83,91)	(0.32,0.52,0.72)	(76,85,94)	0.964
23	40	A0101010000	(566,594,622)	(108,121,135)	(0.28,0.49,0.75)	(64,74,84)	0.941
24	546	A0100000110	(570,603,636)	(96,109,122)	(0.32,0.54,0.88)	(27,35,43)	0.94
25	24	A0000010110	(475,514,552)	(70,80,91)	(0.33,0.52,0.82)	(40,47,55)	0.932
26	338	A0001000001	(573,604,635)	(60,69,79)	(0.59,0.76,0.98)	(54,63,72)	0.919
27	264	A0010010100	(549,602,654)	(51,57,64)	(0.53,0.7,0.98)	(47,56,66)	0.904
28	530	A1000100000	(587,624,661)	(93,101,109)	(0.5,0.69,0.85)	(56,63,70)	0.903
29	14	A0010001000	(574,612,650)	(43,52,63)	(0.61,0.75,0.96)	(30,39,48)	0.893
30	67	A0000001100	(580,628,675)	(60,72,85)	(0.5,0.72,0.97)	(31,38,47)	0.869
31	150	A0100100100	(594,638,682)	(100,110,120)	(0.31,0.55,0.79)	(50,59,67)	0.863
32	294	A1100000000	(586,613,640)	(104,115,126)	(0.34,0.5,0.67)	(22,27,33)	0.859
33	138	A0100010100	(498,538,577)	(86,95,105)	(0.15,0.33,0.55)	(29,36,42)	0.792
34	23	A0000010101	(589,641,692)	(61,69,76)	(0.48,0.66,0.89)	(45,52,60)	0.785
35	278	A1000010000	(496,528,560)	(76,83,91)	(0.32,0.44,0.56)	(33,37,41)	0.785
36	70	A0001000100	(553,594,635)	(43,51,59)	(0.29,0.42,0.58)	(42,49,57)	0.59

According to Table 6, the most efficient portfolio has an efficiency score of 1.45 and contains projects 3, 5, and 9. There are 4 other portfolios with the efficiency scores ranging from 1.3 to 1.5. The two portfolios that ranked first and second contain 3 projects each and differ in only one project. Similarly, the two portfolios that ranked third and fourth contain 3 projects each and have two common projects.

The portfolio that ranked first contains projects 3, 5 and 9. Project 3 is a logical option for every portfolio because it has a very strong chance of success and is prerequisite for a relatively high number of future investments. In fact, project 3 appears in three of the five highest ranked portfolios. The second project in the portfolio that ranked first is project 5 which is also a logical option for every portfolio because it has the second highest efficiency score of 1.36 while it reflects a relatively low risk and contributes considerably to e-readiness. The third project in the portfolio that ranked first is project 9 which has a low price and a low risk but a high efficiency score of 1.35. The portfolio that ranked second contains the same projects as the portfolio that ranked first with project 6 instead of project 5. However, while project 6 has the highest efficiency score of 1.48, it has a risk score of 59.98 which is relatively lower than the risk score of 82.21 for project 5. The portfolio that ranked third contains project 9 (that is also contained in portfolios 1 and 2), project 5 (that is also contained in portfolio 1), project 6 (that is also contained in portfolio 2), and project 2. Project 2 has the lowest risk among all the projects and is prerequisite for a relatively large number of future projects.

5. Discussions and conclusions

This study contributes to the prior literature by providing a new methodology for project portfolio selection (See Fig. 4). This methodology incorporates 4 steps: modeling the problem; evaluating the projects and selecting candidate projects using FDEA; portfolio generation and determining the maximal portfolios; and evaluating the maximal portfolios using FDEA. In this approach, FDEA is used twice: once at the project level and once again at the portfolio level. A number of papers have suggested different methodologies to evaluate portfolios of the projects with interdependencies, while others have taken project uncertainty into consideration. However, there is a lack of portfolio selection methods that concurrently incorporates project uncertainty and interdependencies. Hence, a key contribution of this paper is the construction of a quantitative methodology for selecting portfolios of projects that responds to uncertainty conditions and deals with project interdependencies in terms of resource, outcome and success probability.

Our study has two main managerial implications. Firstly, the portfolio selection methodology proposed in this study incorporates project interdependencies. It implies that before making any investment valuation decision, the project interactions in terms of resources they use and outputs they produce should be evaluated. This responds to IS/IT managers' concern who do not typically consider the big picture of portfolio decision problems. Secondly, the methodology proposed in this paper provides a rational basis for project portfolio selection. This study provides a decision model that objectively takes into account immediate and future value of the projects.

The result of this research demonstrated some preferences of applying FDEA for portfolio selection. Firstly, the FDEA of this study generates a higher number of feasible portfolios compared with the DEA proposed by prior research (e.g. Eilat et al., 2006). This offers the opportunity to examine more portfolios, which becomes an advantage for FDEA. Secondly, FDEA is able to take uncertainty conditions into account (other techniques such as DEA just uses rigid estimates). Thirdly, employing FDEA for portfolio selection ameliorates the deficiency of DEA in differentiating among the most efficient portfolios.

Several methodologies proposed by prior studies on portfolio selection and evaluation are not able to suggest a single 'best' portfolio; rather, they reduce several potential portfolios of projects to a handful of portfolios, presumably of equal 'value'. The decision methodology proposed here is able to determine the optimal portfolio (given the set of established criteria). By using this methodology, decision makers will be able to select the most efficient portfolio(s). In other words, not only does the proposed methodology assist decision makers in eliminating inefficient portfolios, it also helps them choose the most efficient ones.

6. Limitations and future work

The following are the limitations of the method proposed in this study:

- The total number of possible portfolios to be evaluated by the proposed methodology is 2^n (n is the number of candidate projects). In this study, we used 10 candidate projects and enumerated $2^{10}=1024$ portfolios. However, if the number of candidate projects increases, the method becomes less efficient. Assuming that we have 20 candidate projects, the total number of possible portfolios would be $2^{20}=1,048,576$. It is not practical to evaluate this many portfolios. Therefore, it is necessary to perform an initial screening to identify a manageable number of projects to be used in the portfolio construction process.
- Including three or more projects in a portfolio may require a resource input for the portfolio that is significantly smaller than the sum of the inputs required for each project individually or for the projects considered in pairs. The additional project(s) increases the number of alternative portfolios from $\binom{n}{2} = n(n-1)/2$ to $\binom{n}{k} = n!/k!(n-k)!$. If $n=10$ and $k=4$, the number of alternative portfolios increases from 45 to 180; but if k can assume any value, including all 10 projects in one large portfolio, the number of alternative portfolios increases to $2^{10}=1024$.
- The proposed model copes only with pair-wise interactions between projects in input, output, and the chance of success. Therefore, an avenue for future research would be to take into account multiple interactions. If we only consider pair-wise interactions between the projects, the number of interactions we need to analyze would be $\binom{n}{2} = n(n-1)/2$. However, if we consider k_way interactions ($k>2$), we should also take into account 2_, 3_, ..., $k-1$_ way interactions. In other words, if $n=10$ and $k=3$, we need to analyze $\binom{n}{2} + \binom{n}{3} = 45 + 120 = 165$ interactions. Therefore, one avenue of future research would be to consider triple-wise interactions or even higher interactions (i.e. situations

Table 7
The top ten portfolios for α=0, 0.25, 0.5 and 0.75.

Rank	α=0		α=0.25		α=0.5		α=0.75	
	Portfolio number	Attractiveness	Portfolio number	Attractiveness	Portfolio number	Attractiveness	Portfolio number	Attractiveness
1	388	2.2426	388	1.8387	388	1.45	388	1.2315
2	418	2.1906	418	1.7957	418	1.38	308	1.2166
3	164	2.0964	308	1.7581	308	1.35	418	1.2161
4	37	2.0881	164	1.7444	164	1.33	164	1.2071
5	308	2.0866	37	1.7349	37	1.33	37	1.2029
6	148	2.047	148	1.686	148	1.3	178	1.1552
7	261	2.0277	261	1.6697	261	1.27	148	1.1371
8	402	2.0190	21	1.6444	21	1.26	261	1.1354
9	21	1.9985	402	1.6348	194	1.26	194	1.1316
10	194	1.8379	194	1.5644	178	1.21	51	1.1315

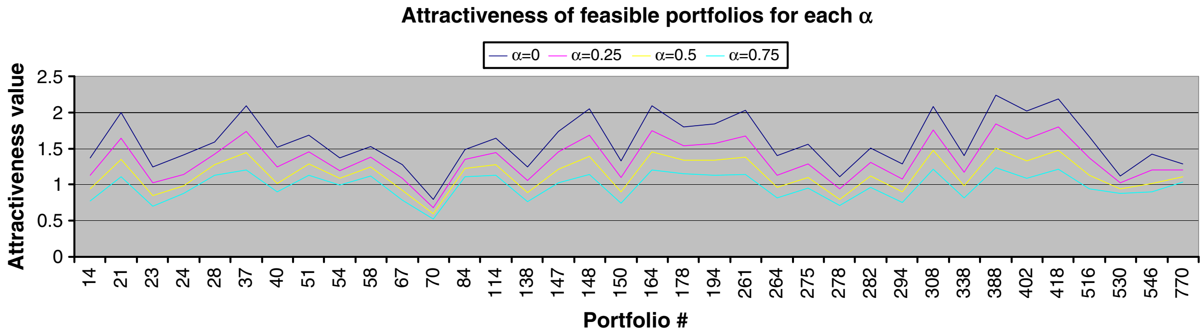

Fig. 5. The efficiency of feasible portfolios for α = 0, 0.25, 0.5 and 0.75.

in which more than two projects have an interaction effect; for example, where including projects *x*, *y*, and *z* which have an interaction with respect to input *i* in a portfolio results in the total value of input *i* required for the portfolio to be different from the sum of input *i* required for each project individually).

In the example provided in this paper, we only considered the mean values and disregarded the variance since the responses returned by the experts did not vary significantly. We consider this acceptable because the focus of this paper was in introducing a methodology that can assist in selecting portfolios of projects (given a set of input, output, and success possibility indices); the way in which estimates for these indices are computed for each project was not the focus of this study.

More research is needed to examine the effects of project interactions and interrelationships. Further research is also required with respect to the qualitative aspects of IS/IT project selection. The problem of quantifying the qualitative factors remains a difficult and sometimes controversial task. For example, we used the Likert scale to assign numbers to linguistic evaluations. But the linguistic evaluations are not subject to the same rules of algebra as numbers on the real line because they do not obey the same axioms. Researchers and practicing managers must be careful not to accept the resulting 'numbers' thoughtlessly. (An autistic boy may score 10 on geometry and 0 on social behavior, but the average of 5 has no meaning whatsoever!)

Acknowledgment

The authors would like to express their gratitude to the anonymous reviewers whose constructive and insightful comments have led to many improvements in this paper.

Appendix 1. Sensitivity analysis

The results presented in Tables 5 and 6 were based on $\alpha = 0.5$ in Eq. (2). In a sensitivity analysis, we studied the effects of different α values, namely $\alpha = 0$, 0.25 and 0.75. The top ten portfolios for each α and their associated efficiency scores are shown in Table 7. The efficient portfolios for each α are relatively similar. For instance, portfolio 388 which includes projects 3, 5, and 9 is the most efficient portfolio for each value of α. Most importantly, portfolios 388, 418, 164, 308, and 37 are the top five portfolios for each α value. According to Fig. 5, the efficiency curve of the feasible portfolios for different α values is very similar. For example, portfolios 388 and 70 have the maximum and minimum amount of efficiency scores for each value of α studied in this sensitivity analysis.

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