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R&D Project Portfolio Selection with Fuzzy Data Envelopment Analysis

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Abstract: R&D investments are becoming increasingly important in the developing world. Companies with limited resources should make the most favorable investments for their own strategies. It is crucial that these investments are transferred to the right projects. It is difficult to make decisions in an environment where there are technical difficulties as well as uncertainties. At this point, it is necessary to decide which projects should be done and which projects should not be done. In this study, project portfolio selection that seeks a systematic solution to this decision, is covered. To solve this problem, data envelopment analysis that can evaluate the parameters without the need to build precedence relationship, is used. Parameters were set after a detailed research. Vagueness that is associated with difficulty of making precise judgment, was included in the model by introducing linguistic variables. Ambiguity that characterizes the situation where there are two or more alternatives, is defined with triangular fuzzy sets and α cut method. Different models are constructed for different extreme cases to solve the ambiguity. The models provide the optimal value regardless of the α value. A sample dataset of 30 projects is created to test the models and observe the results. Optimal parameters weights are found in the models. Full pairwise comparisons are considered while examining the interdependencies. These parameters weights are recalculated according to interdependencies. Using these weights, the efficiency score of each project is calculated for each model. Projects are prioritized for different strategies by using decision making under uncertainty.

Keywords: Project portfolio selection, Data envelopment analysis, Fuzzy sets

Introduction

Technologies are becoming more sophisticated and expanding quickly, causing businesses to depend on research and development (R&D) as a survival strategy to maintain a strong competitive position in the future (Abbassi et al., 2014). The amount of money invested in research and development (R&D) worldwide is astounding. R&D expenditures worldwide were $2.3 trillion in 2019, with around half of that amount coming from business and the remaining amounts from governments and academic institutions. This amount is comparable to roughly 2% of global GDP. Furthermore, during the previous ten years, that yearly investment has increased at a rate of almost 4% (Brennan et al., 2020).

Companies will primarily undertake projects that are chosen based on how well they match with the objectives of the company in order to consolidate R&D investments. However, the risks involved in carrying out R&D projects have shown to have a strong effect since choosing the wrong projects might lead to a loss of resources, both financial and human. When choosing R&D projects in this situation, business strategy's influence is typically appropriately understood. For improved resource use, it is essential to align all projects with the organization's strategic goal (de Souza et al., 2021). A big reason why project selection is such an important topic is that these companies and organizations have a lot of projects to choose from, but they can't choose all of them because of limited resources, staff, time, and other things. As a consequence, a number of projects are

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chosen from among the proposed projects in accordance with the project selection issue that will not only meet the constraint but also provide the firms the most profit (RezaHoseini et al., 2020)

The problem is to choose the optimal project portfolio from a variety of options while taking into account the enterprise's elemental financial, resource, and other external limits. The project portfolio selection (PPS) problem may take into account a variety of goals, but in financial transactions, maximizing profit is always seen as a key goal (Tofighian & Naderi, 2015).

There are several challenges associated with identifying the project portfolio. There can be varied and often conflicting objectives and some of the objectives are qualitative rather than quantitative. There is uncertainty associated with project parameters such as risk and cost. Some projects are heavily interdependent. Constraints such as money, workforce and equipment should be considered in the decision-making process. A portfolio must be balanced for certain factors important to decision makers, such as risk and completion time and the amount of viable portfolios is often very large (Ghasemzadeh et al., 1999)

Uncertainty

It was acknowledged that there are certain traits associated with R&D projects that make the portfolio selection issue more difficult and must be considered throughout the decision-making process. Common evaluation criteria for R&D projects cannot be accurately specified beforehand. There are uncertainties in the areas like capability of the research team, how well the research idea is carried out, and what kind of results it has (Mavrotas & Makryvelios, 2021).

Various studies explore and categorize sources of uncertainty. Uncertainty can be identified into three types: technical, market, and organizational. Technical uncertainty occurs due to lack of know-how knowledge, unreliability of the production process and other factors. Market uncertainty arise due to misunderstanding the customers' needs, types of sales/distribution and the project team's understanding of the relationship between their own products and those of their competitors. The difficulty of understanding customers' needs and translating them into functional features of the product creates market uncertainty. Organizational uncertainties are associated with the dynamics of the organization. Such uncertainties can occur due to as organizational resistance, lack of continuity or persistence, inconsistencies in expectations and measures, changes in strategies, or changes in internal or external partners (Zheng & Carvalho, 2016).

Interdependency

Choosing the optimal portfolio necessitates not just analyzing each project separately, but also how they relate to one another, or how one project affects the others. There is a difference between the overall cost and benefit derived from a portfolio of the projects and the sum of the individual costs and benefits when interdependencies arise and the parameters connected with a given project depend on which other projects have been chosen (Bhattacharyya et al., 2011). Projects often compete with one another for both monetary and non-monetary inputs, but economies of scale may result in savings via collaborative execution. Positive synergies between projects may happen when the sale of one item stimulates an extra demand for another good. On the other hand, negative synergies may occur when there is some degree of rivalry among the projects (Alvarez-García & Fernández-Castro, 2018).

The existing literature has provided a number of different definitions of interdependencies. Interdependencies may be broken down into the following categories; resources, knowledge and market. There are resource interdependencies as a result of the resources that are shared and needs for resource allocation across various projects, including technology. There is knowledge interdependence between projects when one project benefits from the knowledge and skills generated by another project in the portfolio. Market interdependencies arise whenever an existing market is introduced by a new product or if an existing market's expertise is used to the creation of a product that is still in the planning stages (Al Zaabi & Bashir, 2020).

Literature Review

Portfolio decisions are typically arduous by various reasons. First, these choices are intended to help in the realization of a number of different decision goals. Businesses could have a hard time determining how separate projects contribute to shareholder value, so instead, they might rely on a number of proxy characteristics that are simpler to quantify. Second, it is difficult to make an informed judgment about which projects to prioritize since the worth of a given project is often unknown until after it has already begun. For example, a funding organization that provides research funds is required to make decisions about project applications before knowing what the final outcomes of these studies would be. In addition, the recognition of external variables may have a significant impact on the value provided by a product portfolio, which cannot be anticipated at the time product development choices are taken. Third, there is potential for the projects to interact with one another. The combined implementation costs of two R&D projects that share a common research base may be lower than those of the projects taken on individually. Finally, there are a lot of alternate portfolios available and the number of potential portfolios grows exponentially with the number of projects involved (Liesiö et al., 2021).

Zanakis et al. (1995) divided project evaluation and selection methods into descriptive methods, scoring models, Delphi method, pairwise comparison, utility theory, fuzzy set theory, decision analysis, risk analysis, linear regression, correlation analysis, and data envelopment analysis. Chu et al. (1996) divided project selection methods into two main categories as compensatory and non-compensatory methods. Compensatory methods include models such as cost-benefit analysis and the analytical hierarchy process, while non-compensatory methods are divided into multi-criteria decision-making methods and ranking models. Archer and Ghasemzadeh (1999) classified the approaches into five main groups consisting of ad-hoc methods, comparative methods, scoring methods, portfolio matrices and optimization models. Iamratanakul et al. (2008) grouped portfolio selection problems into benefit measurement methods, mathematical programming approaches, cognitive emulation approaches, simulation and heuristics models, real options, and ad-hoc methods.

Mavrotas et al. (2003) applied a two-stage method. The first step consists of multi-criteria decision making that ranks projects according to various criteria. At the end of this step, each alternative was given a score, which was used to eliminate the lowest performing alternatives. In the second step, these scores were used as the coefficients of the objective function to be maximized for a mixed integer linear programming model. Bhattacharyya et al. (2011) presented a fuzzy, three-objective R&D project portfolio selection problem that maximizes the outcome and minimizes the cost and risk involved in the problem, under constraints on resources, budget, interdependencies, output. Tavana et al. (2019) proposed a two-stage approach that combines fuzzy analytic hierarchy process and 0-1 integer programming model. In the first stage, the weights of the criteria were calculated with the fuzzy analytic hierarchy method and the evaluation score of each project was determined. In the second stage, three goals mathematical model was built. This hybrid approach provided the ability to consider both quantitative and qualitative criteria, taking into account monetary constraints and project risks.

Uncertainty

One of the factors that increases the complexity of any real world PPS process is the uncertainty that is an integral part of the process. Lack of expertise and insufficient knowledge are almost always common in investment decision making processes. Using stochastic methods to remove uncertainty is a common and popular approach in many decision-making environments. Stochastic theory applies historical data to handle uncertainty. However, it is not very common to use stochastic theory in a project portfolio selection process, as projects are unique and do not have sufficient historical data. Different techniques have been used to solve uncertainty in project portfolio selection problem. Mavrotas and Pechak (2013) used Monte Carlo simulation with stochastic parameters. Tofighian et al. (2018) considered income as stochastic. Panadero et al. (2018) defined money flows as stochastic.

Because there is a shortage of historical data, it has been common practice to consult with specialists. These specialists, drawing on their own personal experience, offer model values and the variation range that should be anticipated for unknown parameters. This motivates referring to all of these estimates as fuzzy numbers, where the membership function provides insight into the accuracy with which the parameter is being estimated (Perez & Gomez, 2016).

Zadeh (1965) introduced fuzzy sets to eliminate uncertainty. The lack of precise information and insufficient data in the projects are some of the factors that require the application of expert judgments. This is done using fuzzy sets. Fuzzy PPS has been the subject of many studies. Carlsson et al. (2007) developed a fuzzy mixed integer programming model using trapezoidal fuzzy numbers. Riddell and Wallace (2007) used a fuzzy-based approach. Bas (2012) developed a fuzzy 0-1 knapsack model. Perez and Gomez (2016) employed fuzzy constraints in mathematical modeling. Over the years, the need for improvement of fuzzy set theory has emerged as it is applied more and more to real world problems.

Interdependency

Generally, project interdependencies occur when one project's progress is largely or entirely impacted by another project or projects, or, more precisely, when the success of a project relies upon other project or projects. Project-to-project dependencies may arise at a variety of scales, from individual tasks and goals to a group's work or even an entire project. For example, sharing resources among multiple projects will likely result in overall cost savings, while increasing opportunities for generating new knowledge. Increasing connectivity between projects can bring more benefits, however it will be more challenging to select a portfolio (Bathallath et al., 2016).

Ignoring interdependencies results in inefficient solutions and inefficient use of resources. Resource interdependency occurs when the overall cost of a portfolio is not equal to the sum of the costs of the separate projects. Technical interdependencies mainly relate to how one project affects the likelihood that another will succeed. The degree to which the success of one project is contingent upon the completion of another is an example of a technical interdependency. Market interdependencies affect total return of a portfolio. Market interdependencies may either increase or decrease the portfolio's value beyond the sum of its component projects (Schmidt, 1993).

Method

Data Envelopment Analysis (DEA) was developed by Charnes et al. (1978). DEA is a mathematical model that is used to measure the performance of decision making units (DMUs) evaluated by multiple and common inputs and outputs.

$$\max h_0 = \frac{\sum_{r=1}^{s} u_r y_{r0}}{\sum_{i=1}^{m} v_i x_{i0}}$$
$$\frac{\sum_{r=1}^{s} u_r y_{rj}}{\sum_{i=1}^{m} v_i x_{ij}} \leq 1, \qquad \forall j$$
$$u_r, v_i \geq 0, \qquad \forall r, i$$

Assuming that the values of inputs and outputs of DMUs are based on the subjective opinion of d decision makers (k=1, 2, …, d), every decision maker estimates that each DMU consumes m inputs x_{ijk} ($\mathrm{i} = 1, 2, \ldots, \mathrm{m};\ \mathrm{k} = 1, 2, \ldots, \mathrm{d}$) to produce s outputs y_{rjk} ($\mathrm{r} = 1, 2, \ldots, \mathrm{s};\ \mathrm{k} = 1, 2, \ldots, \mathrm{d}$). The geometric mean will be used to combine the d different opinions generated for each criterion. As a result, the CCR model turns into the following model.

$$\max E_0 = \frac{\sum_{r=1}^{s} u_r \left(\prod_{k=1}^{d} y_{r0k}\right)^{1/d}}{\sum_{i=1}^{m} v_i \left(\prod_{k=1}^{d} x_{i0k}\right)^{1/d}}$$

$$\frac{\sum_{r=1}^{s} u_r \left(\prod_{k=1}^{d} y_{rjk}\right)^{1/d}}{\sum_{i=1}^{m} v_i \left(\prod_{k=1}^{d} x_{ijk}\right)^{1/d}} \leq 1, \qquad \forall j$$
$$u_r, v_i \geq \varepsilon, \qquad \forall r, i$$

Tavana et al. (2013) developed a data envelopment analysis model that solved uncertainty for project portfolio selection problem. After solving vagueness and ambiguity, four extreme cases aroused. In our model, we have adopted all fuzzy parameters as triangular fuzzy numbers. Let's assume that each DMU (j=1, 2, …, n) consumes m fuzzy inputs $\tilde{x}_{ij} = (x_{ij}^1, x_{ij}^2, x_{ij}^3)$ to produce s fuzzy outputs $\tilde{y}_{rj} = (y_{rj}^1, y_{rj}^2, y_{rj}^3)$. Using a random α-cut for each triangular fuzzy number, the lower and upper bounds of the membership functions for the inputs and outputs are calculated as follows (Ali et al., 2016):

$$\left(x_{ij}^L\right)_{\alpha_i} = x_{ij}^1 + \alpha_i\left(x_{ij}^2 - x_{ij}^1\right), \qquad \alpha_i \in [0,1]; \;\; i = 1, 2, \ldots, m; \;\; j = 1, 2, \ldots, n$$
$$\left(x_{ij}^U\right)_{\alpha_i} = x_{ij}^3 - \alpha_i\left(x_{ij}^3 - x_{ij}^2\right), \qquad \alpha_i \in [0,1]; \;\; i = 1, 2, \ldots, m; \;\; j = 1, 2, \ldots, n$$

$$\left(y_{rj}^{L}\right)_{\alpha_r} = y_{rj}^1 + \alpha_r\left(y_{rj}^2 - y_{rj}^1\right), \qquad \alpha_r \in [0,1]; \;\; r = 1,2,\dots,s; \;\; j = 1,2,\dots,n$$
$$\left(y_{rj}^{U}\right)_{\alpha_r} = y_{rj}^3 - \alpha_r\left(y_{rj}^3 - y_{rj}^2\right), \qquad \alpha_r \in [0,1]; \;\; r = 1,2,\dots,s; \;\; j = 1,2,\dots,n$$

In the first case, inputs and outputs take the upper bound:

$$\begin{gathered}
\max \lambda \\
\textstyle\sum_{r=1}^{s} u_r \left(y_{rj}^3 - \alpha_r\left(y_{rj}^3 - y_{rj}^2\right)\right) - \lambda\left(\sum_{i=1}^{m} v_i\left(x_{ij}^3 - \alpha_i\left(x_{ij}^3 - x_{ij}^2\right)\right)\right) \geq 0, \;\; \forall j \\
\textstyle\sum_{r=1}^{s} u_r \left(y_{rj}^3 - \alpha_r\left(y_{rj}^3 - y_{rj}^2\right)\right) - \sum_{i=1}^{m} v_i\left(x_{ij}^3 - \alpha_i\left(x_{ij}^3 - x_{ij}^2\right)\right) \leq 0, \;\; \forall j \\
u_r, v_i \geq \varepsilon, \;\; \forall r, i \\
\alpha_i \in [0,1], \;\; \forall i \\
\alpha_r \in [0,1], \;\; \forall r \\
0 \leq \lambda \leq 1
\end{gathered}$$

In the second case, inputs take the lower bound and outputs take the upper bound:

$$\begin{gathered}
\max \lambda \\
\textstyle\sum_{r=1}^{s} u_r \left(y_{rj}^3 - \alpha_r\left(y_{rj}^3 - y_{rj}^2\right)\right) - \lambda\left(\sum_{i=1}^{m} v_i\left(x_{ij}^1 - \alpha_i\left(x_{ij}^2 - x_{ij}^1\right)\right)\right) \geq 0, \;\; \forall j \\
\textstyle\sum_{r=1}^{s} u_r \left(y_{rj}^3 - \alpha_r\left(y_{rj}^3 - y_{rj}^2\right)\right) - \sum_{i=1}^{m} v_i\left(x_{ij}^1 - \alpha_i\left(x_{ij}^2 - x_{ij}^1\right)\right) \leq 0, \;\; \forall j \\
u_r, v_i \geq \varepsilon, \;\; \forall r, i \\
\alpha_i \in [0,1], \;\; \forall i \\
\alpha_r \in [0,1], \;\; \forall r \\
0 \leq \lambda \leq 1
\end{gathered}$$

In the third case, inputs take the upper bound and outputs take the lower bound:

$$\begin{gathered}
\max \lambda \\
\textstyle\sum_{r=1}^{s} u_r \left(y_{rj}^1 - \alpha_r\left(y_{rj}^2 - y_{rj}^1\right)\right) - \lambda\left(\sum_{i=1}^{m} v_i\left(x_{ij}^3 - \alpha_i\left(x_{ij}^3 - x_{ij}^2\right)\right)\right) \geq 0, \;\; \forall j \\
\textstyle\sum_{r=1}^{s} u_r \left(y_{rj}^1 - \alpha_r\left(y_{rj}^2 - y_{rj}^1\right)\right) - \sum_{i=1}^{m} v_i\left(x_{ij}^3 - \alpha_i\left(x_{ij}^3 - x_{ij}^2\right)\right) \leq 0, \;\; \forall j \\
u_r, v_i \geq \varepsilon, \;\; \forall r, i \\
\alpha_i \in [0,1], \;\; \forall i \\
\alpha_r \in [0,1], \;\; \forall r \\
0 \leq \lambda \leq 1
\end{gathered}$$

In the fourth case, inputs and outputs take the lower bound:

$$\begin{gathered}
\max \lambda \\
\textstyle\sum_{r=1}^{s} u_r \left(y_{rj}^1 - \alpha_r\left(y_{rj}^2 - y_{rj}^1\right)\right) - \lambda\left(\sum_{i=1}^{m} v_i\left(x_{ij}^1 - \alpha_i\left(x_{ij}^2 - x_{ij}^1\right)\right)\right) \geq 0, \;\; \forall j \\
\textstyle\sum_{r=1}^{s} u_r \left(y_{rj}^1 - \alpha_r\left(y_{rj}^2 - y_{rj}^1\right)\right) - \sum_{i=1}^{m} v_i\left(x_{ij}^1 - \alpha_i\left(x_{ij}^2 - x_{ij}^1\right)\right) \leq 0, \;\; \forall j \\
u_r, v_i \geq \varepsilon, \;\; \forall r, i \\
\alpha_i \in [0,1], \;\; \forall i \\
\alpha_r \in [0,1], \;\; \forall r \\
0 \leq \lambda \leq 1
\end{gathered}$$

Conflicting rankings may arise for a given decision-making unit due to different α-cutoff levels. Because α levels were not predefined. Finally, the models are non-linear and it will be difficult to find the global optimal value. Due to these problems mentioned, the model proposed by Tavana et al. (2013) were used. To linearize the models, $\beta_r = \alpha_r u_r$ and $\gamma_i = \alpha_i v_i$ equations are modified. After the conversions, the models were still not linear that's why $\delta_i = \gamma_i \lambda$ and $\zeta_i = v_i \lambda$ added to remove the nonlinearity. So, four extreme cases were revised. In the first case, inputs and outputs take the upper bound:

$$\begin{gathered}
\max \lambda \\
\textstyle\sum_{r=1}^{s} u_r y_{rj}^3 - \beta_r\left(y_{rj}^3 - y_{rj}^2\right) - \sum_{i=1}^{m} \zeta_i x_{ij}^3 - \delta_i\left(x_{ij}^3 - x_{ij}^2\right) \geq 0, \;\; \forall j \\
\textstyle\sum_{r=1}^{s} u_r y_{rj}^3 - \beta_r\left(y_{rj}^3 - y_{rj}^2\right) - \sum_{i=1}^{m} v_i x_{ij}^3 - \gamma_i\left(x_{ij}^3 - x_{ij}^2\right) \leq 0, \;\; \forall j \\
u_r, v_i \geq \varepsilon, \;\; \forall r, i \\
0 \leq \beta_r \leq u_r, \;\; \forall r \\
0 \leq \gamma_i \leq v_i, \;\; \forall i \\
0 \leq \zeta_i \leq v_i, \;\; \forall i \\
0 \leq \delta_i \leq v_i, \;\; \forall i \\
0 \leq \lambda \leq 1
\end{gathered}$$

In the second case, inputs take the lower bound and outputs take the upper bound:

$$\max \lambda$$
$$\sum_{r=1}^{s} u_r y_{rj}^3 - \beta_r\left(y_{rj}^3 - y_{rj}^2\right) - \sum_{i=1}^{m} \zeta_i x_{ij}^1 - \delta_i\left(x_{ij}^2 - x_{ij}^1\right) \geq 0, \ \ \forall j$$
$$\sum_{r=1}^{s} u_r y_{rj}^3 - \beta_r\left(y_{rj}^3 - y_{rj}^2\right) - \sum_{i=1}^{m} v_i x_{ij}^1 - \gamma_i\left(x_{ij}^2 - x_{ij}^1\right) \leq 0, \ \ \forall j$$
$$u_r, v_i \geq \varepsilon, \ \ \forall r, i$$
$$0 \leq \beta_r \leq u_r, \ \ \forall r$$
$$0 \leq \gamma_i \leq v_i, \ \ \forall i$$
$$0 \leq \zeta_i \leq v_i, \ \ \forall i$$
$$0 \leq \delta_i \leq v_i, \ \ \forall i$$
$$0 \leq \lambda \leq 1$$

In the third case, inputs take the upper bound and outputs take the lower bound:

$$\max \lambda$$
$$\sum_{r=1}^{s} u_r y_{rj}^1 - \beta_r\left(y_{rj}^2 - y_{rj}^1\right) - \sum_{i=1}^{m} \zeta_i x_{ij}^3 - \delta_i\left(x_{ij}^3 - x_{ij}^2\right) \geq 0, \ \ \forall j$$
$$\sum_{r=1}^{s} u_r y_{rj}^1 - \beta_r\left(y_{rj}^2 - y_{rj}^1\right) - \sum_{i=1}^{m} v_i x_{ij}^3 - \gamma_i\left(x_{ij}^3 - x_{ij}^2\right) \leq 0, \ \ \forall j$$
$$u_r, v_i \geq \varepsilon, \ \ \forall r, i$$
$$0 \leq \beta_r \leq u_r, \ \ \forall r$$
$$0 \leq \gamma_i \leq v_i, \ \ \forall i$$
$$0 \leq \zeta_i \leq v_i, \ \ \forall i$$
$$0 \leq \delta_i \leq v_i, \ \ \forall i$$
$$0 \leq \lambda \leq 1$$

In the fourth case, inputs and outputs take the lower bound:

$$\max \lambda$$
$$\sum_{r=1}^{s} u_r y_{rj}^1 - \beta_r\left(y_{rj}^2 - y_{rj}^1\right) - \sum_{i=1}^{m} \zeta_i x_{ij}^1 - \delta_i\left(x_{ij}^2 - x_{ij}^1\right) \geq 0, \ \ \forall j$$
$$\sum_{r=1}^{s} u_r y_{rj}^1 - \beta_r\left(y_{rj}^2 - y_{rj}^1\right) - \sum_{i=1}^{m} v_i x_{ij}^1 - \gamma_i\left(x_{ij}^2 - x_{ij}^1\right) \leq 0, \ \ \forall j$$
$$u_r, v_i \geq \varepsilon, \ \ \forall r, i$$
$$0 \leq \beta_r \leq u_r, \ \ \forall r$$
$$0 \leq \gamma_i \leq v_i, \ \ \forall i$$
$$0 \leq \zeta_i \leq v_i, \ \ \forall i$$
$$0 \leq \delta_i \leq v_i, \ \ \forall i$$
$$0 \leq \lambda \leq 1$$

Implementation

After a detailed literature research, it was decided to evaluate the models on a total of 9 criteria; cost, return on investment, project plan, research group, technical tasks, strategic objectives, feasibility, subsequent projects and environment. From the parameters selected for evaluation, cost and return on investment are preferred to be kept low in research and development projects. Therefore, these parameters were set as input parameters. For the remaining parameters, it is desired to be kept high. That's why remaining parameters were set as output parameters.

For the evaluation of the determined parameters, the 5-scale evaluation scale was used (Jafarzadeh et al., 2018). This scale consists of very low, low, medium, high and very high values. The parameters were evaluated using these linguistic expressions. It was decided to use triangular fuzzy numbers to describe linguistic expressions. Symmetrical triangular fuzzy numbers are chosen for membership function that are given in Table 1.

Table 1. Membership function

Linguistic variable	Triangular fuzzy variable		
Very low	0	0.17	0.33
Low	0.17	0.33	0.5
Medium	0.33	0.5	0.67
High	0.5	0.67	0.83
Very high	0.67	0.83	1

Results and Discussion

Within the framework of the established model, 9 different parameter values were generated to rank 30 different projects. The models were solved on GAMS. Optimal input and output coefficient values were obtained. For each model, the efficiency score was calculated separately for each decision-making unit by using the optimal parameter weight values:

$$E_j^k = \frac{\sum_{r=1}^{s} u_r^k \tilde{y}_{rj}}{\sum_{i=1}^{m} v_i^k \tilde{x}_{ij}},\ j = 1, 2, \dots, n;\ k = 1, 2, 3, 4$$

Adjoining the Interdependencies

The interdependencies that exist in the project portfolio selection problem, have not yet been considered. Within the scope of this study, 9 parameters characterizing the projects were determined. The cost parameter is used to solve resource interdependencies. The technical tasks parameter is used to analyze technical interdependencies. At the point of evaluation of technical dependencies, it is necessary to include the know-how of the companies. Because, the technical knowledge gained from previous projects will also have a positive impact. Know-how is also included when defining technical interdependencies. In problem definition, the only parameter that characterizes the outcome was chosen as the return on investment parameter. Since the return on investment parameter chosen on the problem does not fully cover the market interdependencies, the market interdependencies were excluded in our model. New methodology that was developed, enables to include all pairwise relation for the interdependencies. At this point, it is foreseen that the decision makers will establish relations and assignments have been made for these data. Evaluation scale for interdependencies is given at Table 2.

Table 2. Scale of interdependencies

Qualitative	Quantitative
0	Non synergy
1	Very low synergy
2	Low synergy
3	Medium synergy
4	High synergy
5	Very high synergy

The values of the cost parameter consumed by each decision-making unit were recalculated including interdependencies as shown below.

$$x_{1j}^{k'} = (x_{1j})(1 - \tau_{1j}),\ \forall j$$

The value defined by τ_{1j} in the equation can be called the total cost interdependence of that project. At this point, this parameter has been calculated as shown below.

$$\tau_{1j} = \sum_{j=1}^{30} (\digamma_{ij}/\varphi)/5,\ \forall i$$

The value of $\digamma_{ij}$ given in the above equation corresponds to the amount of synergy between project i and j. The value of φ shows that how many projects are interdependent. Calculated cost synergies are included in the model using equation below.

$$E_j^{k'} = \frac{\sum_{r=1}^{s} u_r^k \tilde{y}_{rj}}{v_1^k \tilde{x}_{1j}^{k'} + v_2^k \tilde{x}_{2j}},\ j = 1, 2, \dots, n;\ k = 1, 2, 3, 4$$

For the technical tasks' parameter, the weight of the defined criteria was calculated individually and multiplied by the total amount of synergy and its contribution to the total effectiveness score was calculated. The contribution of technical tasks synergy is shown in the equation below.

$$\text{ϙ}_j = \frac{u_3^k \tilde{y}_{3j}}{\sum_{i=1}^{m} v_i^k \tilde{x}_{ij}} (\tau_{2j}),\ \forall j$$

The value defined by τ_{2j} can be called the total synergy of technical tasks for that project. At this point, this parameter has been calculated as shown below.

$$\tau_{2j} = \sum_{j=1}^{30} (\text{ϝ}_{ij}/\varphi)/5\,,\ \forall i$$

The value of ϝ_{ij} given in the above equation corresponds to the amount of synergy between project i and j. The value of φ shows that how many projects are interdependent. The final efficiency score was calculated by including the contribution of the synergy of technical tasks. Efficiency scores, including the interdependencies of each decision-making unit, were calculated by the equation shown below.

$$E_j^{k''} = E_j^{k'} + \text{ϙ}_j,\ \forall j$$

By using decision making methods under uncertainty, priority orders were determined by using optimistic, pessimistic, neutral and robust strategies (Tavana et al., 2013).

Conclusion

With the methodology adopted in this study, data envelopment analysis was used, which includes multiple inputs and outputs and allows them to be solved without defining antecedent weights. Uncertain information arises due to lack of expertise or lack of data. Main characteristics of project portfolio selection that are vagueness and ambiguity were included in the method. Vagueness was included in the model with the help of linguistic expressions. These linguistic expressions used were translated into qualitative expressions with the help of fuzzy triangular numbers. Ambiguity was solved through built different models for extreme cases. After defining the uncertainty and calculating the efficiency scores, interdependencies were also defined. Technical and resource interdependencies were included in the model. The firm's know-how is added into the identification of technical interdependencies. Efficiency scores that were calculated by including interdependencies were ranked for four different types of decision makers using decision making methods under uncertainty.

Recommendations

With this study, a model including uncertainty and interdependencies, which are the main characteristics of the project portfolio selection problem, developed. However, market interdependency is excluded due to the selected parameter values. Therefore, researchers who want to include market dependencies for future studies can choose a different parameter. By including market interdependencies, negative synergies can be defined also. The method developed for the evaluation of negative synergies can be used by updating the interdependency's scale. While defining interdependencies, crisp values were used. In future studies, these definitions can be developed and solved in accordance with fuzzy logic.

Scientific Ethics Declaration

The authors declare that the scientific ethical and legal responsibility of this article published in EPSTEM journal belongs to the authors.

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