Evaluating large, high-technology project portfolios using a novel interval-valued Pythagorean fuzzy set framework: An automated crane project case study

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Abstract

The contemporary organization relies increasingly on developing large, high technology projects in order to gain local and global competitive advantage. Uncertainty and the complexity of project evaluation requires improved and tailored decision making support systems. A new framework for high technology project portfolio evaluation is introduced. Novel development of an interval-valued Pythagorean fuzzy set (IVPFS) approach is shown to accommodate degrees of membership, non-membership and hesitancy in the evaluation process. Developed methods of linear assignment, IVPFS ranking, IVPFS knowledge index, and IVPFS comparison provide a new framework for group evaluation based on a weighting for each decision expert. The framework is developed as a last aggregation which avoids information loss and introduces a new aggregation process. A novel multi-objective model is then introduced to address project portfolio selection while optimizing the value of the portfolio in terms of resilience (the risk of disruption and delays) and skill utilization (assignment of human resources). The applicability of this framework is demonstrated through a case study in high technology portfolio evaluation. The applied case study shows that the presented framework can be applied as the core to a high technology evaluation decision support system.

Keywords: High technology, project portfolio, interval-valued Pythagorean fuzzy sets, evaluation framework under uncertainty, subjective and objective criteria weights, last aggregation, ranking IVPFS, multi-objective model

1. Introduction

The contemporary organization is increasingly structured around projects. It is critical to the success of such an organization that the projects it undertakes align with the organizational goals and maximize the organizational gain (Li et al., 2016). Effective selection of the portfolio of projects an organization undertakes is an important driver of operational efficiency and resources allocation (Chiang and Nunez, 2013). The variety of competing considerations in portfolio selection makes it a non-trivial decision-making problem (Perez et al., 2018; Biancardi and Villani, 2017; Ramalingam, 2018). This complexity is further compounded when the projects are large scale in nature and involve the application of emerging technologies (Mousavi et al., 2015; Moradi et al., 2017; Haghighi et al., 2019).

Large projects are typically more significant to the organization and society in general. They represent substantial investment, extend over several years, and deliver important social and commercial infrastructure (Crosby, 2014; Jafarzadeh et al., 2018). High technology projects inevitably are more speculative, can involve substantial research and development, are more uncertain and ambiguous, and as a consequence they represent especially high risk investment. The high risk is also a complex risk, as it is dependent on a combination of multi-facetted factors, including the technology itself, group dynamics, multi-disciplinary collaboration, often dispersed governance, and integration with a complex network of related critical infrastructure (Crosby, 2012).

In response to the complexity and uncertainty of large, high technology projects there has been increasing interest in the development of effective project evaluation and selection decision-support systems specific to the nature of these projects. For example, Sabzian et al. (2018) introduced a neural network model to evaluate the potential success or failure of large projects. Lu et al. (2017) have applied evidence-based reasoning to address project selection in the high technology equipment manufacturing industry. A decision-support system for high technology enterprise development is the main focus of Chernov and Chernova (2017). Due to the general lack of relevant historical data, vagueness and the strong influence of expert judgment, fuzzy set theory has emerged as an important approach in considering the uncertainty of project selection problems (Mohagheghi et al., 2017a,b). Shan and Sun (2008) used fuzzy mathematical methods to introduce a quantitative measure model to evaluate the risk of high technology investment projects. Kahraman et al. (2009) proposed a fuzzy axiomatic design and fuzzy analytic hierarchy process to select renewable energy alternatives.

Hybrid modeling approaches are now common. Baysal et al. (2015) introduced a two-phase model based on a fuzzy multi-criteria decision-making hybrid approach (FMCDM) to address highly complex project evaluation processes: a fuzzy technique for order of preference by similarity to ideal solution (TOPSIS) to determine a group of candidate projects, followed by applied fuzzy analytic hierarchy process (AHP) to identify the best project from that group. Ji et al. (2015) proposed an integrated fuzzy entropy-weight, multiple criteria decision making (IFEMCDM) model to evaluate project risk for hydropower stations. The IFEMCDM model integrates fuzzy set theory, the entropy weight method and multiple criteria decision making within a risk assessment framework. Tavana et al. (2013) developed a fuzzy group data envelopment analysis model to handle uncertain decision making specifically for high technology projects.

The multi-criteria decision models have taken a variety of forms. Sefair et al. (2017) proposed a mean-semivariance project selection model to investigate oil and gas project portfolio selection. Relich and Pawlewski (2017) presented a fuzzy weighted average method (FWAM) for new product development project portfolio selection, which applied a fuzzy weighted method and neural networks to evaluate projects. The developed FWAM employed criteria related to issues, such as marketing, performance, risk and strategy. Martins et al. (2017) investigated project portfolio selection in the electricity industry by employing multi-criteria decision-making tools to present a web-based decision support system. Lima et al. (2017) applied portfolio theory to attend to the forecast of solar and wind resources. Hummel et al. (2017) addressed research and development investment projects by introducing a multi-criteria resource allocation modeling method. The model employed measuring attractiveness by a categorical based evaluation technique (MACBETH) to minimize the impact of surgical robots in invasive surgical procedures. Aviso et al. (2017) applied a target-oriented robust optimization (TORO) model for project portfolio selection. The developed TORO model was evaluated against two case studies to optimize the selection of engineering measures required to reduce air emissions and remove safety hazards in operational industrial plants. Ghassemi and Amalnick (2018) studied new product development project portfolio selection while addressing reinvestment strategy. Liu et al. (2019) have also applied a data-driven inference model to select research and development projects.

Dealing more specifically with uncertainty has created a research trajectory of its own in order to address project portfolio selection in highly uncertain research and development contexts, Martinez et al. (2018) considered issues such as competing resources allocation policies, the interdependence between tasks and projects, portfolio balancing rules, uncertainty in the overall budget, and the level of resources being requested. Such complex forms of uncertainty required the use of fuzzy triangular numbers and fuzzy programming. The use of fuzzy triangular numbers for multi-criteria decision frameworks was also adopted by Wu et al. (2018) to evaluate large-scale rooftop photovoltaic project portfolio selection. In that case, triangular intuitionistic fuzzy numbers (TIFNs) were used to address the uncertainties. Caglar and Gurel (2018) proposed a two-stage model which first addressed budget allocation decisions and then maximized the total score of supported projects under allocated budgets for the portfolio selection of public research and development projects. Wu et al. (2019) followed with a case study to evaluate another two-stage framework, this time for the rational selection of a portfolio of distributed energy generation projects.

It is evident that the primary focus of previous studies is on the classic (Type 1) application of fuzzy set theory. Type 1 fuzzy sets are characterized by their crisp membership functions in the interval [0, 1]. However, this form is not able to fully support many of the uncertainty types that occur in linguistic descriptions of numerical quantities or in the subjectively expressed knowledge of experts (Bezdek, 2013; Hsu, 2015; Meng et al., 2018; Zavadskas et al., 2017). Interval Type 2 fuzzy sets improve on the classic models in this regard, and Mohagheghi et al. (2017a) have attempted to address high technology project decision making specifically using this more recent form of enhanced fuzzy set. Type 2 fuzzy sets do provide for partial membership expressions, but are still not able to express the degrees of non-membership and hesitancy evident when observing expert decision-making processes in practice. The addition of membership features, non-membership, and incomplete knowledge is possible with intuitionistic fuzzy sets (IFS's) (Atanassov, 1983). However, the IFS method is not able to convey the more comprehensive opinions of experts when, for example, in particular situations the measure of membership and non-membership collectively sum to a value that is larger than 1.

Yager (2013, 2014) developed the Pythagorean fuzzy set (PFS) specifically to handle the situations where the IFS method falls short. PFS is an extension of IFS. The PFS extension improves both the flexibility and applicability of IFS. PFS is able to show not only the extent of the agreement between experts but also the fuzziness of that extent (Szmidt et al., 2014; Xu and Liao, 2014). The interval-valued Pythagorean fuzzy set (IVPFS) improves even further on the original PFS method by applying intervals instead of single values to denote the degrees of membership expressed in such sets.

Despite the significant capability advantage of IVPFS to deal with the particular form of uncertain decision-making typical of large, high technology projects, IVPFS has not previously been applied to such project portfolio selection and evaluation problems. The primary motivations for this paper are then as follows:

- Portfolio selection of large, high technology projects deals with a particular kind of project for which an error in judgement can result in substantial and potentially catastrophic failures. Despite this significant risk, the project portfolio selection literature is relatively weak when it comes to decision-making methods specific to high technology projects. Advancing our capacity to deal with complex decision-making contexts such as this is a key motivation for this study.
- Large and high technology projects typically involve greater levels of uncertainty than more conventional decision-making contexts. Developing and applying decision-support tools that are better able to accommodate and deal with increased uncertainty is paramount. The introduction and use of the IVPFS method in this context seeks to address the evident need for degrees of membership, non-membership and hesitancy to be expressable using intervals. The use of such intervals also provides more flexibility than is possible with intuitionistic sets, since IVPFS's are able to accommodate a larger range of values. This study provides the first application of IVPFS's to the high technology project portfolio selection problem.
- Multi-criteria decision-making problems typically require the criteria to be ranked by domain experts. However, in problems such as high technology project evaluation the domain experts themselves need to be considered as having various levels of importance. It is critical to such problem contexts that the ranking of criteria and the relative importance of each domain expert providing those rankings is appropriately computed and addressed. It is a particular motivation of this study to effectively and efficiently accommodate both criteria and domain experts with different levels of relative importance.
- The characteristically large, high technology project represents a problem with multiple layers and aspects, each of which might otherwise require a distinct decision-making tool. A critical motivation for this study is to develop a single, comprehensive decision-making framework that can successfully incorporate a variety of evaluation and decision-making methods, including linear assignment, criteria and expert weighting, multi-objective modeling and last aggregation processing.

This paper introduces a novel evaluation framework for high technology project and project portfolio selection and evaluation based on IVPFS. In this framework, the concepts of group decision-making, linear assignment, score function, subjective and objective weights of criteria, and subjective and objective weights of decisions are developed to address the particular features of large, high technology projects. The developed framework includes a number of novel contributions:

- A new IVPFS based method of linear assignment is introduced, where the concept of linear assignment is applied and enhanced in order to assign the optimal rankings to project alternatives;
- A novel method for ranking IVPFS's is presented and implemented in the evaluation algorithm;
- An IVPFS knowledge index is introduced and applied to further enhance the weighting process of project evaluation criteria, by developing a weight that is based on the subjective and the objective disciplines of criteria weighting;
- The relative superiority/inferiority of experts is computed and applied to properly handle the weights of decision makers in a novel expert weighting method;
- The framework employs last aggregation, and the aggregation itself is carried out using a specially developed aggregation method;
- A new multi-objective model is presented that addresses portfolio value optimization, resilience optimization and project manager assignment based on skill utilization.

The remainder of this paper is organized as follows: in Section 2 the foundation IVPFS method is presented; Section 3 develops the extended framework proposed for large, high technology project evaluation; Section 4 introduces the novel project portfolio optimization method; Section 5 applies the approach to a demonstration case study in which the best portfolio of projects for research and development investment in new technologies is determined; and Section 6 presents the concluding remarks of the paper.

2. Interval-valued Pythagorean fuzzy sets

What differentiates the PFS from IFS is an extended flexibility and capacity to accommodate vagueness. This advantage is gained by extending the space in which the degrees of membership, non-membership and hesitancy can be depicted (Dorfeshan and Mousavi, 2019). A numerical example to illustrate this advantage is when the degree of membership is equal to $\frac{\sqrt{3}}{2}$ and the degree of non-membership is equal to $\frac{1}{2}$. In this situation, an IFS cannot be utilized since $\frac{\sqrt{3}}{2}+\frac{1}{2}>1$. On the other hand, the PFS is applicable because $\left(\frac{\sqrt{3}}{2}\right)^2+\left(\frac{1}{2}\right)^2\leq 1$. The PFS is able to represent higher degrees of uncertainties and accommodate larger values of vagueness than the IFS. Figure 1 shows graphically the enhanced space of PFS in comparison with IFS (Zhang and Xu, 2014; Yager, 2014; Zhang, 2016).

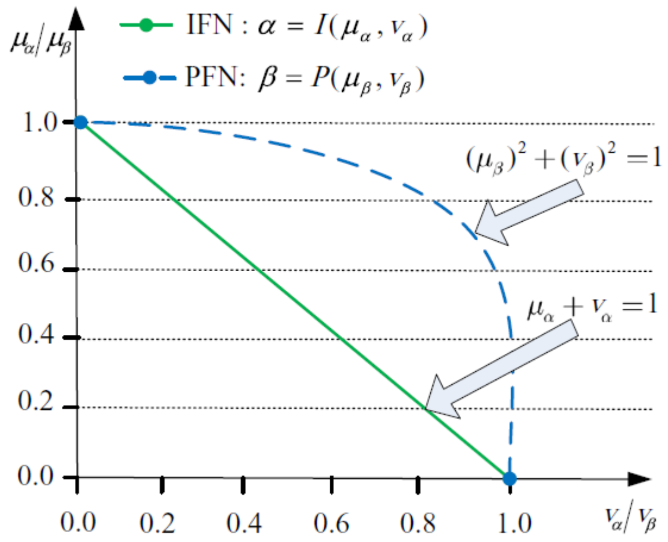

Figure 1. Spaces of PFS and IFS

The following presents the fundamental aspects of IFS and PFS.

S in a universe of discourse (*X*) as an IFS is denoted in the following:

$$S = \{< x, \mu_S(x), \nu_S(x) > | x \in X\} \tag{1}$$

In Eq. (1), $\mu_S: X \to [0,1]$ expresses the value of membership and $\nu_S: X \to [0,1]$ expresses the value of non-membership of element $x \in X$ to the set *S*, respectively. Eq. (2) should hold for any IFS:

$$0 \leq \mu_S(x) + \nu_S(x) \leq 1 \tag{2}$$

A third value called the value of indeterminacy $\pi_S(x)$ is shown in Eq.(3):

$$\pi_S(x) = 1 - \mu_S(x) - \nu_S(x) \tag{3}$$

Atanassov (1983) proposed IFS as an extension to classic fuzzy sets in order to show the values of membership, non-membership and hesitance. Despite this added capability, there are still situations when the values that an alternative like x_i both satisfies and dissatisfies (with respect to attribute L_j), and together result in a value that is larger than 1. To deal with this shortcoming, Yager (2013, 2014) proposed the PFS.

C in a universe of discourse (*X*) is a PFS which can be shown in the following:

$$C = \{< x, \mu_C(x), \nu_C(x) > | x \in X\} \tag{4}$$

In Eq. (4), $\mu_C: X \to [0,1]$ expresses the value of membership and $\nu_C: X \to [0,1]$ denotes the value of non-membership of element $x \in X$ to the set *C*, respectively. Eq. (5) should hold for any PFS:

$$0 \leq \left(\mu_C(x)\right)^2 + \left(\nu_C(x)\right)^2 \leq 1 \tag{5}$$

There is a third value called the indeterminacy value $\pi_C(x)$ which is shown in Eq. (6):

$$\pi_C(x) = \sqrt{1 - \left(\mu_C(x)\right)^2 - \left(\nu_C(x)\right)^2} \tag{6}$$

Peng and Yang (2015) then defined an IVPFS as follows:

Int ([0,1]) denotes the set of all closed subintervals of [0,1] and X is defined as a universe of discourse. Then an IVPFS $\tilde{P}$ in X is defined as follows:

$$\tilde{P} = \{\langle x, \mu_{\tilde{P}}(x), \upsilon_{\tilde{P}}(x)\rangle | x \in X\} \tag{7}$$

In this equation, $\mu_{\tilde{P}}: X \to Int([0,1])(x \in X \to \mu_{\tilde{P}}(x) \subseteq [0,1]$ and $\upsilon_{\tilde{P}}: X \to Int([0,1])(x \in X \to \upsilon_{\tilde{P}}(x) \subseteq [0,1]$ respectively show the membership and non-membership degrees of the element x belonging to X to the set $\tilde{P}$. It should be noted that for every $x \in X, 0 \leq \{sup(\mu_{\tilde{P}}(x))^2 + sup(\upsilon_{\tilde{P}}(x))^2 \leq 1\}$. Moreover, for each $x \in X, \mu_{\tilde{P}}(x)$ and $\upsilon_{\tilde{P}}(x)$ are closed intervals. Their lower and upper bounds are denoted by $\mu_{\tilde{P}}^-(x), \mu_{\tilde{P}}^+(x), \upsilon_{\tilde{P}}^-(x), \upsilon_{\tilde{P}}^+(x)$, respectively. It can be concluded that it is also possible to depict $\tilde{P}$ as follows:

$$\tilde{P} = \{\langle x, [\mu_{\tilde{P}}^-(x), \mu_{\tilde{P}}^+(x)], [\upsilon_{\tilde{P}}^-(x), \upsilon_{\tilde{P}}^+(x)]\rangle | x \in X\} \tag{8}$$

$\tilde{P}$ is subject to the following condition:

$$0 \leq \left(\mu_{\tilde{P}}^+(x)\right)^2 + \left(\upsilon_{\tilde{P}}^+(x)\right)^2 \leq 1 \tag{9}$$

The degree of indeterminacy is defined as follows:

$$\begin{aligned} \pi_{\tilde{P}}(x) &= [\pi_{\tilde{P}}^-(x), \pi_{\tilde{P}}^+(x)] \\ &= \left[\sqrt{1 - \left(\mu_{\tilde{P}}^+(x)\right)^2 - \left(\upsilon_{\tilde{P}}^+(x)\right)^2}, \sqrt{1 - \left(\mu_{\tilde{P}}^-(x)\right)^2 - \left(\upsilon_{\tilde{P}}^-(x)\right)^2}\right] \end{aligned} \tag{10}$$

The score function of $\tilde{P}$ is defined as follows (Peng and Yang, 2015):

$$s(\tilde{p}) = \frac{1}{2}\left[\left(\mu_{\tilde{P}}^+(x)\right)^2 + \left(\mu_{\tilde{P}}^-(x)\right)^2 - \left(\upsilon_{\tilde{P}}^+(x)\right)^2 - \left(\upsilon_{\tilde{P}}^-(x)\right)^2\right], s(\tilde{p}) \in [-1,1] \tag{11}$$

The accuracy function of $\tilde{P}$ is defined as follows (Peng and Yang, 2015):

$$a(\tilde{p}) = \frac{1}{2}\left[\left(\mu_{\tilde{P}}^+(x)\right)^2 + \left(\mu_{\tilde{P}}^-(x)\right)^2 + \left(\upsilon_{\tilde{P}}^+(x)\right)^2 + \left(\upsilon_{\tilde{P}}^-(x)\right)^2\right], a(\tilde{p}) \in [0,1] \tag{12}$$

The hesitancy degree of $\tilde{P}$ is defined as follows (Peng and Yang, 2015):

$$h(\tilde{p}) = \frac{1}{2}\left[1 - \left(\mu_{\tilde{P}}^{+}(x)\right)^{2} - \left(\upsilon_{\tilde{P}}^{+}(x)\right)^{2} + 1 - \left(\mu_{\tilde{P}}^{-}(x)\right)^{2} - \left(\upsilon_{\tilde{P}}^{-}(x)\right)^{2}\right], h(\tilde{p}) \in [0,1] \quad (13)$$

The distance between two IVPFNs $\tilde{p}_1$ and $\tilde{p}_2$ is defined as follows (Peng and Yang, 2015):

$$\begin{aligned} d(\tilde{p}_1, \tilde{p}_2) = \frac{1}{4}(&|(\mu_1^-)^2 - (\mu_2^-)^2| + |(\mu_1^+)^2 - (\mu_2^+)^2| + |(\upsilon_1^-)^2 - (\upsilon_2^-)^2| \\ &+ |(\upsilon_1^+)^2 - (\upsilon_2^+)^2| + |(\pi_1^-)^2 - (\pi_2^-)^2| + |(\pi_1^+)^2 - (\pi_2^+)^2|) \end{aligned} \quad (14)$$

Let $\tilde{p}_1 = ([\mu_1^-, \mu_1^+], [\upsilon_1^-, \upsilon_1^+])$ and $\tilde{p}_2 = ([\mu_2^-, \mu_2^+], [\upsilon_2^-, \upsilon_2^+])$ be two PFNs and $\rho > 0$. PFNs operations applied in this study are based on the following (Peng and Yang, 2015):

$$\begin{aligned} &\tilde{p}_1 \oplus \tilde{p}_2 \\ &= \left(\left[\sqrt{(\mu_1^-)^2 + (\mu_2^-)^2 - (\mu_1^-)^2(\mu_2^-)^2}, \sqrt{(\mu_1^+)^2 + (\mu_2^+)^2 - (\mu_1^+)^2(\mu_2^+)^2}\right], [\upsilon_1^-\upsilon_2^-, \upsilon_1^+\upsilon_2^+]\right); \end{aligned} \quad (15)$$

$$\begin{aligned} &\tilde{p}_1 \otimes \tilde{p}_2 \\ &= \left([\mu_1^-\mu_2^-, \mu_1^+\mu_2^+], \left[\sqrt{(\upsilon_1^-)^2 + (\upsilon_2^-)^2 - (\upsilon_1^-)^2(\upsilon_2^-)^2}, \sqrt{(\upsilon_1^+)^2 + (\upsilon_2^+)^2 - (\upsilon_1^+)^2(\upsilon_2^+)^2}\right]\right); \end{aligned} \quad (16)$$

$$\rho\tilde{p}_1 = \left(\left[\sqrt{1 - (1 - (\mu_1^-)^2)^\rho}, \sqrt{1 - (1 - (\mu_1^+)^2)^\rho}\right], [(\upsilon_1^-)^\rho, (\upsilon_1^+)^\rho]\right) \quad (17)$$

$$\tilde{p}_1{}^\rho = \left([(\mu_1^-)^\rho, (\mu_2^+)^\rho], \left[\sqrt{1 - (1 - (\upsilon_1^-)^2)^\rho}, \sqrt{1 - (1 - (\upsilon_1^+)^2)^\rho}\right]\right) \quad (18)$$

3. An evaluation framework for large, high technology projects

In this section, an evaluation framework is introduced specifically for large, high technology projects. The framework comprises 6 steps and the overall process is represented graphically in Figure 2:

Step 1 A team of experts is formed.

Step 2 Ratings for the alternatives and the weights of criteria are collected from the available data and the expert group.

Step 3 The ratings and weights for each criteria are computed using both the subjective and the objective data obtained at Step 2.

Step 4 The concept of linear assignment is applied to rank the alternatives individually according to the data gathered for each expert.

Step 5 Based on the subjective and the objective data a weight for each expert is computed to provide for an overall group decision outcome.

Step 6 A final ranking and evaluation outcome is determined by applying the new aggregation process.

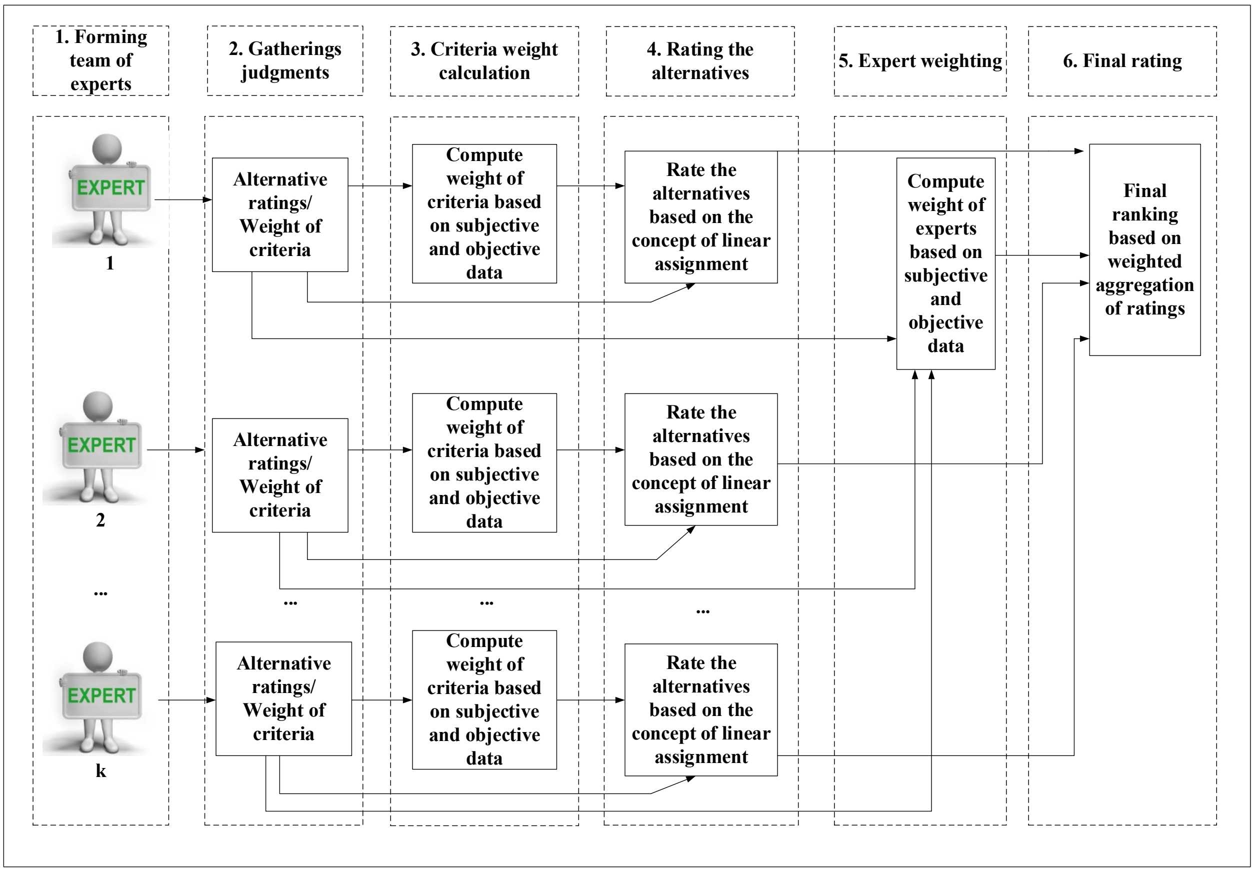

Figure 2. The overall framework process proposed to evaluate large high technology projects

Each step is described in detail as follows:

3.1 Forming a team of experts

Any large high technology project will involve a range of disciplines and multiple groups. The most reliable subjective data will come from the independent responses of a representative team of experts. The starting point for any meaningful evaluation process is therefore to gather together the key different perspectives with a particular focus on the mix of past experience and field of expertise.

3.2 Gathering judgments

This step is achieved with the application of IVPFS. The experts are asked to express their opinions on the degrees of membership, non-membership and hesitancy using two main intervals of membership and non-membership. The hesitancy can be calculated from the other two intervals. It is necessary to constrain the IVPFS within the limitations $(x \in X, 0 \leq \{sup(\mu_{\tilde{P}}(x))^2 + sup(v_{\tilde{P}}(x))^2 \leq 1\})$. Recording opinions can be a relatively straight-forward process using a simple spreadsheet. This also enables the specified limitations to be checked automatically and corrections made where necessary. The recorded values form the following matrices:

$$HTR^k = \left[HTP^k_{\text{ij}}\right], i = 1,2, \dots, m, j = 1,2, \dots, n \tag{19}$$

Where, HTR^k represents the rating matrix of the *k*th expert. HTP^k_{ij} depicts the overall project rating of project *i* (*i*=1,2,…,*m*) against criteria *j* (*j*=1,2,…,*n*). HTP^k_{ij} is an IVPFS and is denoted as follows:

$$HTP^k_{ij} = \left(\left[\mu^-_{htp^k_{ij}}, \mu^+_{htp^k_{ij}}\right], \left[\upsilon^-_{htp^k_{ij}}, \upsilon^+_{htp^k_{ij}}\right]\right) \tag{20}$$

HTP^k_{ij} is an IVPFN. Hence, $\mu^-_{htp^k_{ij}}$ denotes the lower membership degree and $\mu^+_{htp^k_{ij}}$ shows the upper membership degree. Also, lower and upper non-membership degrees are presented by $\upsilon^-_{htp^k_{ij}}$ and $\upsilon^+_{htp^k_{ij}}$, respectively.

The IVPFS approach is also used to determine the relative importance of each criterion. The process to weight criteria is the same process to form and rate the matrices. The following presents the criteria evaluation matrix for subjective data:

$$HTC^k_j = \left(\left[\mu^-_{htc^k_j}, \mu^+_{htc^k_j}\right], \left[\upsilon^-_{htc^k_j}, \upsilon^+_{htc^k_j}\right]\right) \tag{21}$$

Where HTC^k_j denotes the importance of high-technology criteria j expressed by experts *k*. HTC^k_j is an IVPFN. Therefore, $\mu^-_{htc^k_j}$ denotes the lower membership degree and $\mu^+_{htc^k_j}$ shows the upper membership degree. Also, lower and upper non-membership degrees are presented by $\upsilon^-_{htc^k_j}$ and $\upsilon^+_{htc^k_j}$, respectively.

3.3 Criteria weights calculation

In this step of the framework, weights for the evaluation criteria are computed using both the subjective and the objective data. The proposed approach is based on the study of Guo and Zang (2018). Specifically, the knowledge index proposed by Guo and Zang (2018) for IVPFS is applied recursively to compute the importance of each evaluation criteria for the IVPFS. First, the knowledge index of the IVPFS (KIIVPFS) is computed with the following equation:

$$\begin{aligned} KIIVPFS^k_j &= \frac{1}{n}\sum_{i=1}^{n} KIIVPFS\left(\left[\mu^-_{htp^k_{ij}}, \mu^+_{htp^k_{ij}}\right], \left[\upsilon^-_{htp^k_{ij}}, \upsilon^+_{htp^k_{ij}}\right]\right) \\ &= 1 \\ &- \frac{1}{2n}\sum_{i=1}^{n}\left[\left(1 - \frac{1}{2}\left(\left|\mu^-_{htp^k_{ij}} - \upsilon^-_{htp^k_{ij}}\right|\right) + \left|\mu^+_{htp^k_{ij}} - \upsilon^+_{htp^k_{ij}}\right|\right)\right] \\ &\times \left[1 + \frac{1}{2}\left(\pi^-_{htp^k_{ij}} + \pi^+_{htp^k_{ij}}\right)\right] \end{aligned} \tag{22}$$

$KIIVPFS_j^k$ presents the knowledge index of criteria *j* according to the judgments of *k*th domain expert. The recorded judgments of each expert provide the basis on which to determine the value of a KIIVPFS for each criterion, which indicates the relative importance of each criterion. In other words, $KIIVPFS_j^k$ represents the weight of each criterion based on the recorded expert judgments of alternatives and provides an objective weighting of the criteria.

In order to aggregate the recorded criteria values, and thereby determine the relative importance of criteria, $KIIVPFS_j^k$ and HTC_j^k are used to form a novel value that combines the subjective and objective importance data. This value is termed the importance of criteria (IC_j^k), and is obtained as follows:

$$IC_j^k = \left(\begin{array}{c} \left[\sqrt{1-\left(1-\left(\mu_{htc_j^k}^-\right)^2\right)^{KIIVPFS_j^k}}, \sqrt{1-\left(1-\left(\mu_{htc_j^k}^+\right)^2\right)^{KIIVPFS_j^k}} \right], \\ \left[\left(\upsilon_{htc_j^k}^-\right)^{KIIVPFS_j^k}, \left(\upsilon_{htc_j^k}^+\right)^{KIIVPFS_j^k} \right] \end{array} \right) \tag{23}$$

Where IC_j^k denotes the importance of criteria *j* according to the opinions of *k*th expert. This aggregation is performed based on multiplying a crisp value in an IVPFN. The results show IVPFN's that are affected by the values of $KIIVPFS_j^k$. As a result, the outcome considers the subjective and the objective features of the importance of each criterion.

3.4 Candidate evaluation according to each expert

To evaluate the candidates, the recorded judgments are compared. For this comparison a novel measure between IVPFS is presented to yield the condition of each IVPFS versus other such values. The comparison process involves 6 discrete stages:

1 The dominant solution ($\widetilde{DS}$) and the inferior solution ($\widetilde{IS}$) are set.

2 The value of similarity between each HTP_{ij}^k and the dominant solution (dds_{ij}^k) is obtained by means of the following equation:

$$\begin{aligned} dds_{ij}^k\left(HTP_{ij}^k, \widetilde{DS}\right) &= \frac{1}{4}\Bigg(\left| \left(\mu_{htp_{ij}^k}^-\right)^2 - \left(\mu_{\widetilde{DS}}^-\right)^2 \right| + \left| \left(\mu_{htp_{ij}^k}^+\right)^2 - \left(\mu_{\widetilde{DS}}^+\right)^2 \right| \\ &+ \left| \left(\upsilon_{htp_{ij}^k}^-\right)^2 - \left(\upsilon_{\widetilde{DS}}^-\right)^2 \right| + \left| \left(\upsilon_{htp_{ij}^k}^+\right)^2 - \left(\upsilon_{\widetilde{DS}}^+\right)^2 \right| + \left| \left(\pi_{htp_{ij}^k}^+\right)^2 - \left(\pi_{\widetilde{DS}}^-\right)^2 \right| \\ &+ \left| \left(\pi_{htp_{ij}^k}^-\right)^2 - \left(\pi_{\widetilde{DS}}^+\right)^2 \right| \Bigg) \end{aligned} \tag{24}$$

Where $dds_{ij}^k\left(HTP_{ij}^k, \widetilde{DS}\right)$ shows the value of similarity between each HTP_{ij}^k and dominant solution (dds_{ij}^k). This equation employs the principles of distance between two IVPFN's to measure similarity between two IVPF values.

3 The value of similarity between each HTP_{ij}^{k} and the inferior solution (dis_{ij}^{k}) is obtained by means of the following equation:

$$dis_{ij}^{k}\left(HTP_{ij}^{k},\widetilde{IS}\right) = \frac{1}{4}\left(\left|\left(\mu_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\mu_{\widetilde{IS}}^{-}\right)^{2}\right| + \left|\left(\mu_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\mu_{\widetilde{IS}}^{+}\right)^{2}\right| + \left|\left(\upsilon_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\upsilon_{\widetilde{IS}}^{-}\right)^{2}\right| + \left|\left(\upsilon_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\upsilon_{\widetilde{IS}}^{+}\right)^{2}\right| + \left|\left(\pi_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\pi_{\widetilde{IS}}^{-}\right)^{2}\right| + \left|\left(\pi_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\pi_{\widetilde{IS}}^{+}\right)^{2}\right|\right) \tag{25}$$

Where $dis_{ij}^{k}\left(HTP_{ij}^{k},\widetilde{IS}\right)$ shows the value of similarity between each HTP_{ij}^{k} and the inferior solution (dis_{ij}^{k}). This equation employs the principles of distance between two IVPFN's to measure similarity between two IVPF values.

4 Find the point IRP$\left(\min\left(dds_{ij}^{k}\left(HTP_{ij}^{k},\widetilde{DS}\right)\right),\max\left(dis_{ij}^{k}\left(HTP_{ij}^{k},\widetilde{IS}\right)\right)\right)$ as the optimized ideal reference point (IRP).

5 Calculate the total output of HTP_{ij}^{k} (TO_{ij}^{k}) as the distance of each HTP_{ij}^{k} from IRP$\left(\min\left(dds_{ij}^{k}\left(HTP_{ij}^{k},\widetilde{DS}\right)\right),\max\left(dis_{ij}^{k}\left(HTP_{ij}^{k},\widetilde{IS}\right)\right)\right)$ by employing the following:

$$TO_{ij}^{k} = \sqrt{\begin{array}{l}\left[\begin{array}{l}\left(\frac{1}{4}\left(\begin{array}{l}\left|\left(\mu_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\mu_{\widetilde{DS}}^{-}\right)^{2}\right| + \left|\left(\mu_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\mu_{\widetilde{DS}}^{+}\right)^{2}\right| + \left|\left(\upsilon_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\upsilon_{\widetilde{DS}}^{-}\right)^{2}\right| + \\ \left|\left(\upsilon_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\upsilon_{\widetilde{DS}}^{+}\right)^{2}\right| + \left|\left(\pi_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\pi_{\widetilde{DS}}^{-}\right)^{2}\right| + \left|\left(\pi_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\pi_{\widetilde{DS}}^{+}\right)^{2}\right|\end{array}\right)\right) \\ -\min\left(\frac{1}{4}\left(\begin{array}{l}\left|\left(\mu_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\mu_{\widetilde{DS}}^{-}\right)^{2}\right| + \left|\left(\mu_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\mu_{\widetilde{DS}}^{+}\right)^{2}\right| + \left|\left(\upsilon_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\upsilon_{\widetilde{DS}}^{-}\right)^{2}\right| + \\ \left|\left(\upsilon_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\upsilon_{\widetilde{DS}}^{+}\right)^{2}\right| + \left|\left(\pi_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\pi_{\widetilde{DS}}^{-}\right)^{2}\right| + \left|\left(\pi_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\pi_{\widetilde{DS}}^{+}\right)^{2}\right|\end{array}\right)\right)\end{array}\right]^{2} + \\ \left[\begin{array}{l}\left(\frac{1}{4}\left(\begin{array}{l}\left|\left(\mu_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\mu_{\widetilde{IS}}^{-}\right)^{2}\right| + \left|\left(\mu_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\mu_{\widetilde{IS}}^{+}\right)^{2}\right| + \left|\left(\upsilon_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\upsilon_{\widetilde{IS}}^{-}\right)^{2}\right| + \\ \left|\left(\upsilon_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\upsilon_{\widetilde{IS}}^{+}\right)^{2}\right| + \left|\left(\pi_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\pi_{\widetilde{IS}}^{-}\right)^{2}\right| + \left|\left(\pi_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\pi_{\widetilde{IS}}^{+}\right)^{2}\right|\end{array}\right)\right) - \\ \max\left(\frac{1}{4}\left(\begin{array}{l}\left|\left(\mu_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\mu_{\widetilde{IS}}^{-}\right)^{2}\right| + \left|\left(\mu_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\mu_{\widetilde{IS}}^{+}\right)^{2}\right| + \left|\left(\upsilon_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\upsilon_{\widetilde{IS}}^{-}\right)^{2}\right| + \\ \left|\left(\upsilon_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\upsilon_{\widetilde{IS}}^{+}\right)^{2}\right| + \left|\left(\pi_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\pi_{\widetilde{IS}}^{-}\right)^{2}\right| + \left|\left(\pi_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\pi_{\widetilde{IS}}^{+}\right)^{2}\right|\end{array}\right)\right)\end{array}\right]^{2}\end{array}} \tag{26}$$

Where, TO_{ij}^{k} shows the total output of HTP_{ij}^{k} according to the value of IRP. This equation applies the concept of distance between two distance-based crisp values to compute the performance of each HTP_{ij}^{k}.

6 Rank the values of HTP_{ij}^{k} in increasing order of TO_{ij}^{k}. In case two values end up with the exact value of TO_{ij}^{k}, compute the following to rank the numbers in increasing order of alternative total output (ATO_{ij}^{k}).

$$\begin{aligned} ATO_{ij}^{k} = \frac{1}{4}\Bigg(& \left|\left(\mu_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\mu_{\widetilde{DS}}^{-}\right)^{2}\right| + \left|\left(\mu_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\mu_{\widetilde{DS}}^{+}\right)^{2}\right| + \left|\left(\upsilon_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\upsilon_{\widetilde{DS}}^{-}\right)^{2}\right| \\ & + \left|\left(\upsilon_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\upsilon_{\widetilde{DS}}^{+}\right)^{2}\right| + \left|\left(\pi_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\pi_{\widetilde{DS}}^{-}\right)^{2}\right| + \left|\left(\pi_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\pi_{\widetilde{DS}}^{+}\right)^{2}\right|\Bigg) \\ & - \min\Bigg(\frac{1}{4}\Bigg(\left|\left(\mu_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\mu_{\widetilde{DS}}^{-}\right)^{2}\right| + \left|\left(\mu_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\mu_{\widetilde{DS}}^{+}\right)^{2}\right| + \left|\left(\upsilon_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\upsilon_{\widetilde{DS}}^{-}\right)^{2}\right| \\ & + \left|\left(\upsilon_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\upsilon_{\widetilde{DS}}^{+}\right)^{2}\right| + \left|\left(\pi_{htp_{ij}^{k}}^{+}\right)^{2} - \left(\pi_{\widetilde{DS}}^{-}\right)^{2}\right| + \left|\left(\pi_{htp_{ij}^{k}}^{-}\right)^{2} - \left(\pi_{\widetilde{DS}}^{+}\right)^{2}\right|\Bigg)\Bigg) \end{aligned} \quad (27)$$

ATO_{ij}^{k} compares two HTP_{ij}^{k} values that have the same TO_{ij}^{k}. This equation presents an alternative value to further investigate the values of two alternatives that have the same TO_{ij}^{k}.

Given the outcome of the previous step it is now possible to rank HTP_{ij}^{k} in accordance with the values of TO_{ij}^{k}. These results are then used to generate the necessary matrices, with the fuzziness of the process remaining intact and the candidate projects ranked relative to each criterion. Thus, for each expert, one rank frequency matrix RFM^{k} is obtained. This non-negative square (m×m) matrix comprises elements rfm_{il}^{k} that represent the number of times that a candidate project is ranked lth according to each criterion. The following presents a matrix of RFM^{k}:

$$RFM^{k} = \left[rfm_{\mathrm{il}}^{k}\right], i = 1,2,\dots,m, l = 1,2,\dots,L. \quad (28)$$

In this matrix, rfm_{il}^{k} denotes the number of times that candidate project *i* is ranked as the *l*th alternative according to the judgments of the *k*th domain expert.

A weighted rank frequency matrix based on the values of (IC_{j}^{k}) is then computed (ICRFM^{k}):

$$\mathrm{ICRFM}^{k} = \left[\mathrm{ICRFM}_{\mathrm{il}}^{k}\right], i = 1,2,\dots,M, l = 1,2,\dots,L. \quad (29)$$

Where $\mathrm{ICRFM}_{il}^{k} = \sum_{j \in lth} IC_{j}^{k}$

ICRFM_{il}^{k} denotes the degree of concordance among all criteria in evaluating the *i*th candidate *l*th for *k*th domain expert. In this process, it is possible to end up with σ candidates with the same evaluation according to a given criterion. The original evaluation can then be parted into σ! equalized rankings. As a result, each of the rankings will receive the importance value of 1/ σ! (Chen, 2013).

To reach a ranking of alternatives, the rating of each project is determined so that the value of $\sum_{l=1}^{m} d\left(\mathrm{ICRFM}_{il}^{k}\right)$ is maximized. Here, d denotes the defuzzified value which is extended based on Kahraman et al. (2017). The following linear model is formed to assign candidate projects to ranking positions:

$$\max\sum_{i=1}^{m}\sum_{l=1}^{m}\frac{1}{2}\left(\sqrt{\frac{\mu^{+}_{\mathrm{ICRFM}^{k}_{il}}+\mu^{-}_{\mathrm{ICRFM}^{k}_{il}}}{2}}-\left(\frac{\upsilon^{+}_{\mathrm{ICRFM}^{k}_{il}}+\upsilon^{-}_{\mathrm{ICRFM}^{k}_{il}}}{2}\right)^{2}\right).\beta^{k}_{il} \tag{30}$$

Subject to:

$$\sum_{l=1}^{m}\beta^{k}_{il}=1, i=1,2,\ldots,m \tag{31}$$

$$\sum_{i=1}^{m}\beta^{k}_{il}=1, l=1,2,\ldots,m \tag{32}$$

$$\beta^{k}_{il}=0\ or\ 1\ for\ all\ i\ and\ k \tag{33}$$

This model (30-33) is based on the principles of linear assignment and the goal is to assign each alternative to a ranking. β^{k}_{il} is a binary variable which is equal to 1 when the candidate project *i* is ranked as *l*th according to *k*th expert judgment, and 0 otherwise. Eq. (30) maximizes the outcome of the model by assigning each alternative to a ranking that has the best value of ICRFM^{k}_{il}. Eq. (31) ensures that candidate project *i* is assigned to only one position *l*. Eq. (32) ensures that each ranking position *l* is accessible for just one candidate project *i*. This step results in each candidate project being evaluated according to the opinions of each expert. P^{k}_{i} is applied to denote the position of candidate project *i* in accordance with the opinions of *k*th expert.

3.3 Expert weighting

In order to aggregate the evaluation results it is necessary to consider the weights associated with each expert. This will enhance the efficiency of the aggregation process. Thus, a process developed from the work of Gupta et al. (2018) is proposed to compute the relative importance of experts on the basis of the recorded judgments.

The superiority of *k*th expert (S^k) versus other experts (*o*) is computed using the following:

$$\begin{aligned} S^{k}=\frac{1}{4}\Bigg\{&\sum_{i}\sum_{j}\sum_{k\neq O}\max\left(\mu^{-}_{htp^{k}_{ij}}-\mu^{-}_{htp^{o}_{ij}},0\right)+\sum_{i}\sum_{j}\sum_{k\neq O}\max\left(\mu^{+}_{htp^{k}_{ij}}-\mu^{+}_{htp^{o}_{ij}},0\right)\\ &+\sum_{i}\sum_{j}\sum_{k\neq O}\max\left(\vartheta^{-}_{htp^{k}_{ij}}-\vartheta^{-}_{htp^{o}_{ij}},0\right)\\ &+\sum_{i}\sum_{j}\sum_{k\neq O}\max\left(\vartheta^{+}_{htp^{k}_{ij}}-\vartheta^{+}_{htp^{o}_{ij}},0\right)\\ &+\sum_{i}\sum_{j}\sum_{k\neq O}\max\left(\pi^{-}_{htp^{k}_{ij}}-\pi^{-}_{htp^{o}_{ij}},0\right)\\ &+\sum_{i}\sum_{j}\sum_{k\neq O}\max\left(\pi^{+}_{htp^{k}_{ij}}-\pi^{+}_{htp^{o}_{ij}},0\right)\Bigg\}\end{aligned} \tag{34}$$

Then, the inferiority of *k*th expert (IF^k) versus other experts (*o*) is computed using the following:

$$IF^k = \frac{1}{4}\left\{\sum_i \sum_j \sum_{k \neq O} \max\left(\mu^-_{htp^o_{ij}} - \mu^-_{htp^k_{ij}}, 0\right) + \sum_i \sum_j \sum_{k \neq O} \max\left(\mu^+_{htp^o_{ij}} - \mu^+_{htp^k_{ij}}, 0\right) + \sum_i \sum_j \sum_{k \neq O} \max\left(\vartheta^-_{htp^o_{ij}} - \vartheta^-_{htp^k_{ij}}, 0\right) + \sum_i \sum_j \sum_{k \neq O} \max\left(\vartheta^+_{htp^o_{ij}} - \vartheta^+_{htp^k_{ij}}, 0\right) + \sum_i \sum_j \sum_{k \neq O} \max\left(\pi^-_{htp^o_{ij}} - \pi^-_{htp^k_{ij}}, 0\right) + \sum_i \sum_j \sum_{k \neq O} \max\left(\pi^+_{htp^o_{ij}} - \pi^+_{htp^k_{ij}}, 0\right)\right\} \tag{35}$$

The obtained values are applied in the following mathematical model to compute the importance of each expert (EI^k). To address subjective data in this process, the experts are asked to provide the acceptable limits of importance for each expert. In other words, experts are asked to suggest the least and the highest degree of importance that they believe should be given to each expert. The following presents the weight assignment model:

$$Z_1 = \max \epsilon \left(\sum_{k=1}^{T} \left(\frac{1}{4} \left\{ \sum_i \sum_j \sum_{k \neq O} \max\left(\mu^-_{htp^k_{ij}} - \mu^-_{htp^o_{ij}}, 0\right) + \sum_i \sum_j \sum_{k \neq O} \max\left(\mu^+_{htp^k_{ij}} - \mu^+_{htp^o_{ij}}, 0\right) + \sum_i \sum_j \sum_{k \neq O} \max\left(\vartheta^-_{htp^k_{ij}} - \vartheta^-_{htp^o_{ij}}, 0\right) + \sum_i \sum_j \sum_{k \neq O} \max\left(\vartheta^+_{htp^k_{ij}} - \vartheta^+_{htp^o_{ij}}, 0\right) + \sum_i \sum_j \sum_{k \neq O} \max\left(\pi^-_{htp^k_{ij}} - \pi^-_{htp^o_{ij}}, 0\right) + \sum_i \sum_j \sum_{k \neq O} \max\left(\pi^+_{htp^k_{ij}} - \pi^+_{htp^o_{ij}}, 0\right) \right\} \right) (EI^k) \right) + (1 - \epsilon) \left(- \left(\sum_{k=1}^{T} \frac{1}{4} \left\{ \sum_i \sum_j \sum_{k \neq O} \max\left(\mu^-_{htp^o_{ij}} - \mu^-_{htp^k_{ij}}, 0\right) + \sum_i \sum_j \sum_{k \neq O} \max\left(\mu^+_{htp^o_{ij}} - \mu^+_{htp^k_{ij}}, 0\right) + \sum_i \sum_j \sum_{k \neq O} \max\left(\vartheta^-_{htp^o_{ij}} - \vartheta^-_{htp^k_{ij}}, 0\right) + \sum_i \sum_j \sum_{k \neq O} \max\left(\vartheta^+_{htp^o_{ij}} - \vartheta^+_{htp^k_{ij}}, 0\right) + \sum_i \sum_j \sum_{k \neq O} \max\left(\pi^-_{htp^o_{ij}} - \pi^-_{htp^k_{ij}}, 0\right) + \sum_i \sum_j \sum_{k \neq O} \max\left(\pi^+_{htp^o_{ij}} - \pi^+_{htp^k_{ij}}, 0\right) \right\} \right) (EI^k) \right) \tag{36}$$

Subject to:

$$\sum_{k=1}^{T} EI^k = 1 \tag{37}$$

$$EI^k \in S, \qquad \forall k \in T \tag{38}$$

$$EI^k > 0 \tag{39}$$

$$0 \leq \epsilon \leq 1 \tag{40}$$

In this model, EI^k is the decision variable that denotes the importance of expert *k*. ϵ shows the importance of each term in the objective function. In other words, this parameter can be adjusted to set the importance of the superiority and inferiority in the process. S denotes the feasible region. *T* shows the set of group of experts. Eq. (36) sets the weights in a way that maximum superiority and minimum inferiority is reached. Eq. (37) sets the total value of weights to 1 and Eq. (38) expresses the acceptable limits of importance for each expert judgment. Eq. (40) shows the acceptable range of ϵ which is used to express the preference on superiority or inferiority in the process.

3.6 Overall evaluation

After computing the evaluations and the values of importance for each expert, it is necessary to aggregate the results. In this step, a novel aggregation process is introduced. This is an extended method based on the aggregation process (Zavadskas et al., 2014). The following is utilized to aggregate the outcome of this process:

$$AR_i = \left(\theta_1\left(\sum_{k=1}^{T}\left(P_i^k\right)EI^k\right)\right) + \left(\theta_2\prod_{k=1}^{T}{P_i^k}^{EI^k}\right) + \left(\theta_3\frac{k}{\sum_{k=1}^{T}\frac{1}{\left(P_i^k\right)EI^k}}\right) \tag{41}$$

Eq. (41) is based on the principles of three different averaging techniques. In the aggregation process of Zavadaskas et al. (2014), two averaging techniques were used. Here, the third term in Eq. (41) is added to enhance the aggregation process. This enhancement is reached by addressing another perspective in the aggregation process. AR_i denotes the aggregated project ranking *i*, θ_g ($0<\theta_g<1$, *g* =1,2,3) shows the importance of three approaches in the aggregation process, and $\theta_1 + \theta_2 + \theta_3 = 1$. *g* shows the set of aggregation methods. As mentioned, P_i^k denotes the position of candidate project *i* in accordance with the opinions of *k*th expert and EI^k expresses the importance of *k*th expert.

4. An illustration of the method

At this stage of the study, a new multi-objective mathematical model is presented that is especially suited to large, high technology project portfolio selection. In order to resolve the model, fuzzy goal programming (FGP) is applied (Arkan, 2014). The following presents the notations adopted for this section:

The following sets are presented:

i=1, 2,…,*m*, set of projects,

e=1, 2,…,*E*, Set of project managers,

st, set of short-term projects,

mt, set of medium-term projects,

lt, set of long-term projects,

ME, set of projects having mutual exclusiveness relationship,

CO, set of projects which are a compulsory inclusion in the portfolio, The following parameters are introduced:

AR_i, aggregated rating value of project *i*;

$\widetilde{PMS}_{ei}$, an IVPFN denoting the skill of project manager *e* if assigned to project *i*;

$\widetilde{dis}_i$, an IVPFN denoting the risk of delay and disruption for high technology project *i;*

Min_I, minimum level of permitted capital for the portfolio;

Max_I, maximum level of permitted capital for the portfolio;

Min_{Pr}, minimum number of available high technology project personnel;

Max_{Pr}, maximum number of available high technology project personnel;

C_i, required capital of project *i*;

Pr_i, required high technology personnel of project *i;*

C_{st_i}, required capital of short-term project *i*;

C_{mt_i}, required capital of medium-term project *i*;

C_{lt_i}, required capital of long-term project *i*;

Res, resilience of high-technology portfolio;

α, β and γ, values denoting the weight of investment by time horizon.

The following decision variables are introduced:

x_i, binary decision variable showing selection of project *i*;

y_{ei}, binary decision variable for assigning project manager *e* to high-technology project *i*;

$$Obj_1 = \min \sum_{i=1}^{m} AR_i x_i \tag{42}$$

$$Obj_2 = \max \sum_{i=1}^{m} \frac{1}{2}\left(\sqrt{\frac{\mu^{+}_{PMS_{ei}} + \mu^{-}_{PMS_{ei}}}{2}} - \left(\frac{\upsilon^{+}_{PMS_{ei}} + \upsilon^{-}_{PMS_{ei}}}{2}\right)^2\right). y_{ei} \tag{43}$$

$$Obj_3 = \min \sum_{i=1}^{m} \frac{1}{2}\left(\sqrt{\frac{\mu^{+}_{dis_i} + \mu^{-}_{dis_i}}{2}} - \left(\frac{\upsilon^{+}_{dis_i} + \upsilon^{-}_{dis_i}}{2}\right)^2\right) x_i \tag{44}$$

Subject to:

$$Min_I \leq \sum_{i=1}^{n} C_i x_i \leq Max_I \tag{45}$$

$$Min_{PR} \leq \sum_{i=1}^{n} PR_i x_i \leq Max_{PR} \tag{46}$$

$$\sum_{st\in short-term} C_{st_i}x_i \le \frac{\alpha}{1}\sum_{i=1}^{N} C_i x_i \tag{47}$$

$$\sum_{mt\in mid-term} C_{mt_i}x_i \le \frac{\beta}{1}\sum_{i=1}^{N} C_i x_i \tag{48}$$

$$\sum_{lt\in long-term} C_{lt_i}x_i \le \frac{\gamma}{1}\sum_{i=1}^{N} C_i x_i \tag{49}$$

$$\alpha+\beta+\gamma=1 \tag{50}$$

$$\sum_{e} y_{ei} = x_i, \forall i \in m \tag{51}$$

$$x_i \ne x_i^{''} \qquad for\ i=1,2,\dots,n;\ (i,i'') \in ME \tag{52}$$

$$x_i = 1 \qquad for\ i=1,2,\dots,n;\ \forall i \in CO \tag{53}$$

$$x_i = \begin{cases} 0 \text{ if project } i \text{ is rejected} \\ 1 \text{ if project } i \text{ is selected} \end{cases} \tag{54}$$

$$y_{ei} = \begin{cases} 1 \text{ if project manager } e \text{ is assigned to project } i \\ \qquad\qquad 0 \text{ otherwise} \end{cases} \tag{55}$$

Eq. (42) maximizes the value of a selected portfolio of large, high technology projects. The values for each project are obtained in the previous section. Eq. (43) maximizes the utilized skills of high technology project managers. One of the objectives of this model is to maximize the overall skill level when assigning project managers to the projects. Eq. (44) minimizes the risk of delay and disruption in the particular portfolio. To be clear, the resilience of the projects must be balanced against the potential for unwanted and surprising events. This balance is an important factor that can decide the success or otherwise of the entire portfolio. This important consideration is addressed in the third objective function. Eq. (45) keeps the budget of a particular portfolio within the set acceptable limits. Eq. (46) does the same for personnel. Eqs. (47)-(50) can be used to attend to the short, mid and long term plans of the organization in terms of project selection. Eqs. (51) links the decision variables. Eq. (52) shows the mutual exclusivity of the relationships between projects. Eq. (53) is added to deal with situations where a given project must be included in the portfolio for external reasons. Finally, Eqs. (54) and (55) show the nature of the decision variables.

In order to solve this multi-objective model of large, high technology project portfolio selection, mathematical programming is utilized. The following notations are described in the following:

G $(g = 1,2,3)$, set of objective functions $(Obj_1,\ Obj_2,\ Obj_3)$;

U_g, upper bound of objective function g;

L_g, lower bound of objective function g;

d_g, the difference between the upper and lower bounds of each objective function;

w_g, weight of each objective function;

Ω_g decision variable denoting the optimality of objective function g;

Ω, decision variable denoting the optimality of the model;

$$\max \Omega + \left(\sum_{g \in G} w_g \Omega_g\right) \tag{56}$$

Subject to:

$$\sum_{i=1}^{m} AR_i x_i + \Omega_1 d_1 \le U_1 \tag{57}$$

$$-\left(\sum_{i=1}^{m} \frac{1}{2}\left(\sqrt{\frac{\mu^{+}_{PMS_{ei}} + \mu^{-}_{PMS_{ei}}}{2}} - \left(\frac{\upsilon^{+}_{PMS_{ei}} + \upsilon^{-}_{PMS_{ei}}}{2}\right)^2\right).y_{ei}\right) + \Omega_2 d_2 \le -L_2 \tag{58}$$

$$\sum_{i=1}^{m} \frac{1}{2}\left(\sqrt{\frac{\mu^{+}_{dis_i} + \mu^{-}_{dis_i}}{2}} - \left(\frac{\upsilon^{+}_{dis_i} + \upsilon^{-}_{dis_i}}{2}\right)^2\right) x_i + \Omega_3 d_3 \le U_3 \tag{59}$$

$$Min_I \le \sum_{i=1}^{n} C_i x_i \le Max_I \tag{60}$$

$$Min_{PR} \le \sum_{i=1}^{n} PR_i x_i \le Max_{PR} \tag{61}$$

$$\sum_{st \in short-term} C_{st_i} x_i \le \frac{\alpha}{\mu} \sum_{i=1}^{N} C_i x_i \tag{62}$$

$$\sum_{mt \in mid-term} C_{mt_i} x_i \le \frac{\beta}{\mu} \sum_{i=1}^{N} C_i x_i \tag{63}$$

$$\sum_{lt \in long-term} C_{lt_i} x_i \le \frac{\gamma}{\mu} \sum_{i=1}^{N} C_i x_i \tag{64}$$

$$\alpha + \beta + \gamma = \mu \tag{65}$$

$$\sum_{e} y_{ei} = x_i, \forall i \in m \tag{66}$$

$$x_i \ne x_i^{''} \qquad for\ i = 1,2,\dots,n; (i, i'') \in K \tag{67}$$

$$x_i = 1 \qquad for\ i = 1,2,\dots,n; \forall i \in L \tag{68}$$

$$x_i = \begin{cases} 0 \text{ if project } i \text{ is rejected} \\ 1 \text{ if project } i \text{ is selected} \end{cases} \tag{69}$$

$$y_{ei} = \begin{cases} 1 \text{ if project manager } e \text{ is assigned to project } i \\ 0 \qquad \text{otherwise} \end{cases} \tag{70}$$

$$\Omega \le \Omega_g, \forall g \in G \tag{71}$$

Eq. (56) optimizes the value of Ω in addition to moving the value of Ω_g in the optimality direction. This approach optimizes the overall value of objective functions in addition to the individual objective functions. Eqs. (57), (58) and (59) compute the values of Ω_1, Ω_2 and Ω_3, respectively. Eq. (71) sets the relationship between Ω and Ω_g.

5. A demonstration of the method applied to a large, high technology project evaluation and project portfolio optimization case study

In this section, in order to demonstrate the application of the proposed selection method, a case study of an established logistics service provider is presented. The chosen organization is mainly involved in the provision of maritime logistics and transportation services. The organization is active in a number of ports and is currently seeking to improve its specialized training for staff, make more efficient use of the available resources, and is strategically revising the overall business and operational activities.

A key initiative is to improve the use of resources and service efficiency by implementing high technology port handling and operating systems. This includes the possibility of automating the activities of port related equipment, such as traditional gantry cranes and more mobile gantry cranes. For example, remote crane operations and control systems permit operators to be stationed centrally in a control room, rather than located on each crane individually. Automated guided vehicles can also be considered for dealing with the movement of containers between the quay and the container yard. The development of such automation has been shown to result in reduced operational costs and improved health and safety performance. Further, enhancing the terminal operating system and developing a more comprehensive solution that integrates the entire chain of port activities is also of keen interest. Indeed, the organization has investigated at least five competing high technology project proposals. Figures 3 and 4 provide an impression of the kind of equipment and situations that characterize the organization. Due to confidentiality agreements, specific details of the actual projects cannot be provided, but they are of a scale and level of technology transformation representative of large, high technology projects. For the purposes of this case study, the projects will be simply referred to as HTP_1, HTP_2, HTP_3, HTP_4 and HTP_5.

Figure 3. Typical gantry cranes in use by the case study organization

Figure 4. Typical rubber tyred gantry crane in use by the case study organization

5.1 *Forming a team of experts*

In order to determine and rank the best portfolio of projects from the 5 candidates already considered (HTP_1, HTP_2, HTP_3, HTP_4 and HTP_5) a team of experts is formed comprising: an information technology expert, a technical expert, and a financial development expert. Each expert has a minimum of 10 years of experience in their respective fields. The evaluation criteria were set by the organization as technical feasibility (HTC_1), improving equipment productivity (HTC_2), reducing terminal time (HTC_3), and enhancing service satisfaction (HTC_4).

5.2 *Gathering judgments*

Each expert member of the team was first tasked with making a rating judgment of each candidate project against each assessment criteria. The relative importance of each evaluation criterion was also rated. In order to better address the uncertainty of this complex decision-making process, preliminary knowledge of the IVPFS was provided to the team and they were then required to express their own values of agreement and disagreement using intervals subject to $\left(\mu_C(x)\right)^2 + \left(\nu_C(x)\right)^2 \leq 1$. Table 1 shows the ratings derived through this process. Table 2 shows the relative importance of the evaluation criteria as they were also obtained.

Table 1. Ratings of proposed projects versus evaluation criteria

E_1	HTC_1	HTC_2	HTC_3	HTC_4
HTP_1	$\begin{pmatrix}[0.2,0.4],\\ [0.7,0.75]\end{pmatrix}$	$\begin{pmatrix}[0.4,0.45],\\ [0.6,0.65]\end{pmatrix}$	$\begin{pmatrix}[0.56,0.6],\\ [0.45,0.48]\end{pmatrix}$	$\begin{pmatrix}[0.6,0.65],\\ [0.45,0.48]\end{pmatrix}$
HTP_2	$\begin{pmatrix}[0.7,0.75],\\ [0.25,0.28]\end{pmatrix}$	$\begin{pmatrix}[0.65,0.68],\\ [0.15,0.18]\end{pmatrix}$	$\begin{pmatrix}[0.55,0.58],\\ [0.45,0.5]\end{pmatrix}$	$\begin{pmatrix}[0.65,0.69],\\ [0.45,0.48]\end{pmatrix}$

HTP_3	([0.3,0.35],[0.65,0.68])	([0.5,0.51],[0.58,0.59])	([0.14,0.42],[0.57,0.62])	([0.54,0.56],[0.55,0.57])
HTP_4	([0.65,0.7],[0.3,0.35])	([0.62,0.65],[0.2,0.23])	([0.6,0.65],[0.25,0.3])	([0.6,0.65],[0.5,0.52])
HTP_5	([0.4,0.45],[0.6,0.62])	([0.55,0.57],[0.45,0.48])	([0.45,0.48],[0.52,0.58])	([0.58,0.62],[0.45,0.5])
E_2	HTC_1	HTC_2	HTC_3	HTC_4
HTP_1	([0.35,0.38],[0.5,0.55])	([0.45,0.55],[0.3,0.4])	([0.45,0.55],[0.6,0.63])	([0.63,0.68],[0.7,0.72])
HTP_2	([0.63,0.69],[0.25,0.28])	([0.75,0.82],[0.23,0.25])	([0.8,0.82],[0.23,0.25])	([0.55,0.58],[0.65,0.69])
HTP_3	([0.38,0.42],[0.45,0.48])	([0.41,0.43],[0.5,0.52])	([0.5,0.52],[0.54,0.56])	([0.6,0.65],[0.4,0.45])
HTP_4	([0.7,0.8],[0.3,0.35])	([0.7,0.78],[0.25,0.28])	([0.7,0.75],[0.25,0.27])	([0.74,0.8],[0.45,0.55])
HTP_5	([0.4,0.45],[0.5,0.52])	([0.45,0.49],[0.42,0.56])	([0.56,0.64],[0.4,0.45])	([0.65,0.75],[0.5,0.59])
E_3	HTC_1	HTC_2	HTC_3	HTC_4
HTP_1	([0.23,0.26],[0.55,0.63])	([0.26,0.36],[0.55,0.74])	([0.5,0.55],[0.35,0.42])	([0.42,0.51],[0.52,0.62])
HTP_2	([0.65,0.74],[0.4,0.45])	([0.55,0.58],[0.45,0.48])	([0.6,0.69],[0.4,0.48])	([0.8,0.84],[0.23,0.28])
HTP_3	([0.28,0.31],[0.5,0.52])	([0.32,0.39],[0.54,0.6])	([0.48,0.52],[0.48,0.5])	([0.45,0.55],[0.47,0.5])
HTP_4	([0.6,0.7],[0.45,0.5])	([0.7,0.78],[0.4,0.45])	([0.58,0.63],[0.42,0.45])	([0.35,0.38],[0.65,0.69])
HTP_5	([0.35,0.36],[0.55,0.58])	([0.38,0.48],[0.6,0.65])	([0.52,0.59],[0.5,0.52])	([0.85,0.89],[0.2,0.25])

Table 2. Importance of evaluation criteria

	HTC_1	HTC_2	HTC_3	HTC_4
E_1	([0.65,0.69],[0.55,0.59])	([0.78,0.85],[0.22,0.42])	([0.65,0.69],[0.45,0.49])	([0.55,0.65],[0.45,0.56])
E_2	([0.7,0.75],[0.22,0.35])	([0.77,0.82],[0.25,0.31])	([0.69,0.75],[0.45,0.55])	([0.45,0.48],[0.51,0.59])
E_3	([0.55,0.7],[0.25,0.5])	([0.75,0.79],[0.29,0.39])	([0.75,0.78],[0.25,0.35])	([0.63,0.69],[0.24,0.29])

At this stage of the case study it is worth noting how the proposed IVPFS approach compares with the IFS approach from which it is developed. Given the fact that for IFS's $0 \leq \mu_s(x) + \nu_s(x) \leq 1$ should hold, most of the values from Tables 1 and 2 could not be evaluated using IFS. For example, considering the input of the first expert for the first project, the first criteria values are 0.4 and 0.75, which when combined represent a value that is greater than 1, and thereby fail to satisfy the given IFS constraints. Indeed in this instance the values for the second criteria (0.45 and 0.65), third criteria (0.6 and 0.48), and fourth criteria (0.65 and 0.48) all fall outside the given constraints. Given an equivalent situation is likely for a significant proportion of such problem cases, the use of any standard IFS method will be unable to accommodate many of the cases to be encountered. However, the IVPFS method is specifically designed to provide the flexibility and scope required in order to deal with these and a range of such values.

5.3 Criteria weight computations

To utilize weights which have the characteristics of the subjective and the objective data, a knowledge index for each criterion is computed. The obtained value is then applied to form a new value which denotes the relative importance for the evaluation process. Table 3 presents the knowledge index and the resulting weights.

Table 3. The values of $KIIVPFS_j^k$

	HTC_1	HTC_2	HTC_3	HTC_4
E_1	0.42	0.55	0.71	0.8
E_2	0.62	0.57	0.56	0.77
E_3	0.58	0.61	0.8	0.49

Table 4. The values of IC_j^k

	HTC_1	HTC_2	HTC_3	HTC_4
E_1	$\begin{pmatrix}[0.45,0.48],\\ [0.77,0.8]\end{pmatrix}$	$\begin{pmatrix}[0.63,0.71],\\ [0.43,0.61]\end{pmatrix}$	$\begin{pmatrix}[0.57,0.6],\\ [0.56,0.59]\end{pmatrix}$	$\begin{pmatrix}[0.5,0.59],\\ [0.62,0.49]\end{pmatrix}$
E_2	$\begin{pmatrix}[0.93,0.96],\\ [0.01,0.03]\end{pmatrix}$	$\begin{pmatrix}[0.96,0.97],\\ [0.01,0.03]\end{pmatrix}$	$\begin{pmatrix}[0.91,0.95],\\ [0.1,0.18]\end{pmatrix}$	$\begin{pmatrix}[0.76,0.79],\\ [0.07,0.13]\end{pmatrix}$
E_3	$\begin{pmatrix}[0.43,0.57],\\ [0.44,0.66]\end{pmatrix}$	$\begin{pmatrix}[0.63,0.67],\\ [0.46,0.55]\end{pmatrix}$	$\begin{pmatrix}[0.69,0.72],\\ [0.32,0.42]\end{pmatrix}$	$\begin{pmatrix}[0.47,0.52],\\ [0.49,0.54]\end{pmatrix}$

5.4 Proposed project evaluation according to each expert

The ranking is carried out according to the ranking method for IVPFS presented above. Table 5 presents the results for the first expert.

Table 5. The results of ranking

		HTP_1	HTP_2	HTP_3	HTP_4	HTP_5
HTC_1	ATO_{ij}^k	0.66	0.03	0.56	0.08	0.46
	$Ranking$	5	1	4	2	3
HTC_2	ATO_{ij}^k	0.48	0.04	0.39	0.08	0.25
	$Ranking$	5	1	4	2	3
HTC_3	ATO_{ij}^k	0.24	0.25	0.45	0.1	0.38
	$Ranking$	2	3	5	1	4
HTC_4	ATO_{ij}^k	0.22	0.19	0.35	0.26	0.24
	$Ranking$	2	1	5	4	3

Matrices of RFM^k and $ICRFM^k$ are then made based on the obtained rankings. The matrix for Expert 1 is formed as follows:

$$RFM^k = \begin{vmatrix} 0 & 2 & 0 & 0 & 2 \\ 3 & 0 & 1 & 0 & 0 \\ 0 & 0 & 0 & 2 & 2 \\ 1 & 2 & 0 & 1 & 0 \\ 0 & 0 & 3 & 1 & 0 \end{vmatrix} \tag{73}$$

$$ICRFM^k = \begin{vmatrix} 0 & IC_3^1 + IC_4^1 & 0 & 0 & IC_1^1 + IC_2^1 \\ IC_1^1 + IC_2^1 + IC_4^1 & 0 & IC_3^1 & 0 & 0 \\ 0 & 0 & 0 & IC_1^1 + IC_2^1 & IC_3^1 + IC_4^1 \\ IC_3^1 & IC_1^1 + IC_2^1 & 0 & IC_4^1 & 0 \\ 0 & 0 & IC_1^1 + IC_2^1 + IC_4^1 & IC_3^1 & 0 \end{vmatrix} \tag{74}$$

The results for each expert are applied to form the following mathematical model which ranks the proposed projects in accordance with the principles of the linear assignment method. The following presents the model for Expert 1:

$$\begin{aligned} \max z = {} & 0.03x_{11} + 0.8x_{12} + 0x_{13} + 0x_{14} + 0.04x_{15} + 0.039x_{21} + 0.032x_{22} \\ & + 0.62x_{23} + 0.04x_{24} + 0.04x_{25} + 0x_{31} + 0x_{32} + 0.04x_{33} \\ & + 0.77x_{34} + 0.04x_{35} + 0.73x_{41} + 0x_{42} + 0.35x_{43} + 0.44x_{44} \\ & + 0.44x_{45} + 0.03x_{51} + 0.8x_{52} + 0x_{53} + 0x_{54} + 0.04x_{55} \end{aligned} \tag{75}$$

$$x_{11} + x_{12} + x_{13} + x_{14} + x_{15} = 1 \tag{76}$$

$$x_{21} + x_{22} + x_{23} + x_{24} + x_{25} = 1 \tag{77}$$

$$x_{31} + x_{32} + x_{33} + x_{34} + x_{35} = 1 \tag{78}$$

$$x_{41} + x_{42} + x_{43} + x_{44} + x_{45} = 1 \tag{79}$$

$$x_{51} + x_{52} + x_{53} + x_{54} + x_{55} = 1 \tag{80}$$

$$x_{11} + x_{21} + x_{31} + x_{41} + x_{51} = 1 \tag{81}$$

$$x_{12} + x_{22} + x_{32} + x_{42} + x_{52} = 1 \tag{82}$$

$$x_{13} + x_{23} + x_{33} + x_{43} + x_{53} = 1 \tag{83}$$

$$x_{14} + x_{24} + x_{34} + x_{44} + x_{54} = 1 \tag{84}$$

$$x_{15} + x_{25} + x_{35} + x_{45} + x_{55} = 1 \tag{85}$$

$$x_{ij} \begin{cases} 1, if\ x_i\ is\ assigned\ to\ position\ j \\ \quad 0, otherwise \end{cases} \tag{86}$$

Solving the model for each expert results in rankings which are based on their respective judgements. In Table 6 the rankings according to the judgements of each expert are presented.

Table 6. Ranking of each expert

Expert	HTP_1	HTP_2	HTP_3	HTP_4	HTP_5
E_1	5	1	4	2	3
E_2	5	2	4	1	3
E_3	5	2	4	1	3

5.5 Determining the importance of each expert

In order to aggregate the results of different experts, it is necessary to address the importance of each expert in the aggregation process, by computing a weighting for each expert. The inferiority and superiority values for each expert are computed, and the obtained values are used to form the following model. Solving this model derives the degree of importance to be assigned to each expert. The model is presented as follows:

$$\max\left(0.5(0.681EI^1 + 0.592EI^2 + 0.626EI^3)\right) + \left(-0.5(0.675EI^1 + 0.611EI^2 + 0.615EI^3)\right) \quad (87)$$

$$EI^1 + EI^2 + EI^3 = 1 \quad (88)$$

$$EI^k > 0.25, k = 1,2,3 \quad (89)$$

$$EI^k < 0.7, k = 1,2,3 \quad (90)$$

The upper and lower bounding values for weighting the experts are set by the team of experts. Table 7 presents the importance of each expert according to their degree of superiority and inferiority.

Table 7. The values of Inferiority, Superiority and EI^k

Expert	Inferiority	Superiority	EI^k
E_1	0.681	0.675	0.25
E_2	0.592	0.611	0.25
E_3	0.626	0.615	0.5

5.6 Aggregating the evaluation results

The rankings and values of the importance of experts obtained are then used to form the overall assessment value for each proposed project. The results are depicted in Table 8. In order to carry out a sensitivity analysis for the aggregation process, different values are assigned to θ_1, θ_2 and θ_3 (depicted as *A* to *F* in the table). Figure 5 presents the same derived values in the form of a comparison chart.

Table 8. The overall ranking of projects

$A: \theta_1 = 0.4, \theta_2 = 0.3, \theta_3 = 0.3$	HTP_1	HTP_2	HTP_3	HTP_4	HTP_5
Score	3.95	1.33	3.16	0.96	2.37
Ranking	5	2	4	1	3
$B: \theta_1 = 0.3, \theta_2 = 0.4, \theta_3 = 0.3$	HTP_1	HTP_2	HTP_3	HTP_4	HTP_5
Score	3.95	1.32	3.16	0.96	2.37
Ranking	5	2	4	1	3
$C: \theta_1 = 0.3, \theta_2 = 0.3, \theta_3 = 0.4$	HTP_1	HTP_2	HTP_3	HTP_4	HTP_5
Score	3.6	1.2	2.88	0.88	2.16
Ranking	5	2	4	1	3
$D: \theta_1 = 1, \theta_2 = 0, \theta_3 = 0$	HTP_1	HTP_2	HTP_3	HTP_4	HTP_5
Score	5	1.75	4	1.25	3
Ranking	5	2	4	1	3
$E: \theta_1 = 0, \theta_2 = 1, \theta_3 = 0$	HTP_1	HTP_2	HTP_3	HTP_4	HTP_5
Score	5	1.68	4	1.18	3
Ranking	5	2	4	1	3
F: $\theta_1 = 0, \theta_2 = 0, \theta_3 = 1$	HTP_1	HTP_2	HTP_3	HTP_4	HTP_5
Score	1.5	0.42	1.2	0.375	0.9
Ranking	5	2	4	1	3

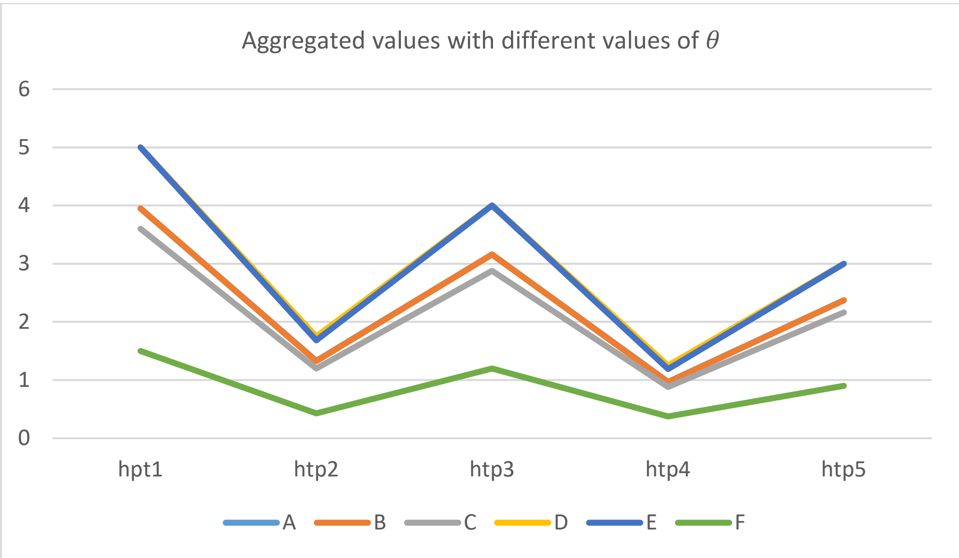

Figure 5. Results of sensitivity analysis of the project evaluation process

5.7 *Allocating a portfolio of projects*

A mathematical programming method is then used to yield the optimal portfolio of high technology projects. Table 9 presents the applied parameters of the mathematical model for the first objective which is finding the portfolio based on the scores obtained in the previous section. Table 10 presents the scores of PMS_{ei}. Table 11 presents the values denoting the risk of disruption for each project, including the capital budget and personnel risks for each project.

Table 9. The overall ranking score of projects

HTP_1	HTP_2	HTP_3	HTP_4	HTP_5
3.95	1.33	3.16	0.96	2.37

Table 10. The values of PMS_{ei} when addressing project manager assignment

	HTP_1	HTP_2	HTP_3	HTP_4	HTP_5
PMS1	$\begin{pmatrix}[0.45,0.55],\\ [0.35,0.4]\end{pmatrix}$	$\begin{pmatrix}[0.65,0.73],\\ [0.45,0.61]\end{pmatrix}$	$\begin{pmatrix}[0.32,0.42],\\ [0.6,0.7]\end{pmatrix}$	$\begin{pmatrix}[0.23,0.43],\\ [0.65,0.75]\end{pmatrix}$	$\begin{pmatrix}[0.61,0.66],\\ [0.23,0.41]\end{pmatrix}$
PMS2	$\begin{pmatrix}[0.65,0.75],\\ [0.35,0.45]\end{pmatrix}$	$\begin{pmatrix}[0.25,0.45],\\ [0.55,0.75]\end{pmatrix}$	$\begin{pmatrix}[0.68,0.78],\\ [0.42,0.52]\end{pmatrix}$	$\begin{pmatrix}[0.61,0.71],\\ [0.12,0.32]\end{pmatrix}$	$\begin{pmatrix}[0.64,0.74],\\ [0.31,0.38]\end{pmatrix}$
PMS3	$\begin{pmatrix}[0.48,0.68],\\ [0.43,0.53]\end{pmatrix}$	$\begin{pmatrix}[0.45,0.55],\\ [0.75,0.8]\end{pmatrix}$	$\begin{pmatrix}[0.35,0.55],\\ [0.64,0.81]\end{pmatrix}$	$\begin{pmatrix}[0.65,0.78],\\ [0.23,0.42]\end{pmatrix}$	$\begin{pmatrix}[0.71,0.81],\\ [0.36,0.41]\end{pmatrix}$
PMS4	$\begin{pmatrix}[0.73,0.83],\\ [0.22,0.32]\end{pmatrix}$	$\begin{pmatrix}[0.68,0.82],\\ [0.25,0.45]\end{pmatrix}$	$\begin{pmatrix}[0.78,0.82],\\ [0.25,0.38]\end{pmatrix}$	$\begin{pmatrix}[0.7,0.78],\\ [0.41,0.52]\end{pmatrix}$	$\begin{pmatrix}[0.35,0.45],\\ [0.55,0.65]\end{pmatrix}$
PMS5	$\begin{pmatrix}[0.32,0.52],\\ [0.65,0.78]\end{pmatrix}$	$\begin{pmatrix}[0.73,0.86],\\ [0.25,0.35]\end{pmatrix}$	$\begin{pmatrix}[0.55,0.75],\\ [0.25,0.42]\end{pmatrix}$	$\begin{pmatrix}[0.18,0.31],\\ [0.45,0.61]\end{pmatrix}$	$\begin{pmatrix}[0.74,0.82],\\ [0.41,0.49]\end{pmatrix}$

Table 11. Risk of disruption, required capital budget and personnel of high technology projects

Project	Risk of disruption	Required capital budget	Required personnel
HTP_1	([0.42,0.53], [0.27,0.41])	20	12
HTP_2	([0.61,0.65], [0.42,0.54])	12	10
HTP_3	([0.23,0.41], [0.61,0.71])	18	15
HTP_4	([0.62,0.71], [0.35,0.52])	16	14
HTP_5	([0.71,0.75], [0.45,0.51])	17	11

The following multi-objective model is formed:

$$Obj_1 = \min \sum_{i=1}^{m} 3.95x_1 + 1.33x_2 + 3.16x_3 + 0.96x_4 + 2.37x_5 \tag{91}$$

$$Obj_2 = \max \sum_{i=1}^{m} \frac{1}{2}\left(\sqrt{\frac{0.45+0.55}{2}} - \left(\frac{0.35+0.4}{2}\right)^2\right).y_{11} + \frac{1}{2}\left(\sqrt{\frac{0.65+0.75}{2}} - \left(\frac{0.35+0.45}{2}\right)^2\right).y_{12} \tag{92}$$

$$+\frac{1}{2}\left(\sqrt{\frac{0.48+0.68}{2}} - \left(\frac{0.43+0.53}{2}\right)^2\right)y_{13} + \frac{1}{2}\left(\sqrt{\frac{0.73+0.83}{2}} - \left(\frac{0.22+0.32}{2}\right)^2\right)y_{14}$$

$$+\frac{1}{2}\left(\sqrt{\frac{0.32+0.52}{2}} - \left(\frac{0.65+0.78}{2}\right)^2\right)y_{15} + \frac{1}{2}\left(\sqrt{\frac{0.65+0.73}{2}} - \left(\frac{0.45+0.61}{2}\right)^2\right).y_{21}$$

$$+\frac{1}{2}\left(\sqrt{\frac{0.25+0.45}{2}} - \left(\frac{0.55+0.75}{2}\right)^2\right).y_{22} + \frac{1}{2}\left(\sqrt{\frac{0.45+0.55}{2}} - \left(\frac{0.75+0.8}{2}\right)^2\right)y_{23}$$

$$+\frac{1}{2}\left(\sqrt{\frac{0.68+0.82}{2}} - \left(\frac{0.25+0.45}{2}\right)^2\right)y_{24} + \frac{1}{2}\left(\sqrt{\frac{0.73+0.86}{2}} - \left(\frac{0.25+0.35}{2}\right)^2\right)y_{25}$$

$$+\frac{1}{2}\left(\sqrt{\frac{0.32+0.42}{2}} - \left(\frac{0.6+0.7}{2}\right)^2\right).y_{31} + \frac{1}{2}\left(\sqrt{\frac{0.68+0.78}{2}} - \left(\frac{0.42+0.52}{2}\right)^2\right).y_{32}$$

$$+\frac{1}{2}\left(\sqrt{\frac{0.35+0.55}{2}} - \left(\frac{0.64+0.81}{2}\right)^2\right)y_{33} + \frac{1}{2}\left(\sqrt{\frac{0.78+0.82}{2}} - \left(\frac{0.25+0.38}{2}\right)^2\right)y_{34}$$

$$+\frac{1}{2}\left(\sqrt{\frac{0.55+0.75}{2}} - \left(\frac{0.25+0.42}{2}\right)^2\right)y_{35} + \frac{1}{2}\left(\sqrt{\frac{0.23+0.43}{2}} - \left(\frac{0.65+0.75}{2}\right)^2\right).y_{41}$$

$$+\frac{1}{2}\left(\sqrt{\frac{0.61+0.71}{2}} - \left(\frac{0.12+0.32}{2}\right)^2\right).y_{42} + \frac{1}{2}\left(\sqrt{\frac{0.65+0.78}{2}} - \left(\frac{0.23+0.42}{2}\right)^2\right)y_{43}$$

$$+\frac{1}{2}\left(\sqrt{\frac{0.7+0.78}{2}} - \left(\frac{0.41+0.52}{2}\right)^2\right)y_{44} + \frac{1}{2}\left(\sqrt{\frac{0.18+0.31}{2}} - \left(\frac{0.45+0.61}{2}\right)^2\right)y_{45}$$

$$+\frac{1}{2}\left(\sqrt{\frac{0.61+0.66}{2}} - \left(\frac{0.23+0.41}{2}\right)^2\right).y_{51} + \frac{1}{2}\left(\sqrt{\frac{0.64+0.74}{2}} - \left(\frac{0.31+0.38}{2}\right)^2\right).y_{52}$$

$$+\frac{1}{2}\left(\sqrt{\frac{0.71+0.81}{2}} - \left(\frac{0.36+0.41}{2}\right)^2\right)y_{53} + \frac{1}{2}\left(\sqrt{\frac{0.35+0.45}{2}} - \left(\frac{0.55+0.65}{2}\right)^2\right)y_{54}$$

$$+\frac{1}{2}\left(\sqrt{\frac{0.74+0.82}{2}} - \left(\frac{0.41+0.49}{2}\right)^2\right)y_{55}$$

$$Obj_3 = \min \sum_{i=1}^{m} \frac{1}{2}\left(\sqrt{\frac{0.42 + 0.53}{2}} - \left(\frac{0.27 + 0.41}{2}\right)^2\right) x_1 + \frac{1}{2}\left(\sqrt{\frac{0.61 + 0.65}{2}} - \left(\frac{0.42 + 0.54}{2}\right)^2\right) x_2 + \frac{1}{2}\left(\sqrt{\frac{0.23 + 0.41}{2}} - \left(\frac{0.61 + 0.71}{2}\right)^2\right) x_3 + \frac{1}{2}\left(\sqrt{\frac{0.62 + 0.71}{2}} - \left(\frac{0.35 + 0.52}{2}\right)^2\right) x_4 + \frac{1}{2}\left(\sqrt{\frac{0.71 + 0.75}{2}} - \left(\frac{0.45 + 0.51}{2}\right)^2\right) x_5 \tag{93}$$

Subject to:

$$15 \leq \sum_{i=1}^{n} 20x_1 + 12x_2 + 18x_3 + 16x_4 + 17x_5 \leq 70 \tag{94}$$

$$25 \leq \sum_{i=1}^{n} 12x_1 + 10x_2 + 15x_3 + 14x_4 + 11x_5 \leq 85 \tag{95}$$

$$\sum_{e} y_{ei} = x_i, \forall i \in m \tag{96}$$

$$\sum_{i} y_{ei} = x_i, \forall e \in E \tag{97}$$

$$x_i = \begin{cases} 0 \text{ if project } i \text{ is rejected} \\ 1 \text{ if project } i \text{ is selected} \end{cases} \tag{98}$$

$$y_{ei} = \begin{cases} 1 \text{ if project manager } e \text{ is assigned to project } i \\ 0 \text{ otherwise} \end{cases} \tag{99}$$

First, the model is solved separately for each objective function and the values of U_i and L_i are set. Table 12 presents the results.

Table 12. High-technology project portfolios with each objective function

	X1	*X2*	*X3*	*X4*	*X5*	U_i
Objective 1	1	1	1	0	1	10.81
Objective 2	0	1	1	1	1	1.53
Objective 3	0	1	1	1	1	1.55
	X1	*X2*	*X3*	*X4*	*X5*	L_i
Objective 1	0	0	0	1	1	3.33
Objective 2	0	1	1	0	0	0.15
Objective 3	1	0	0	1	0	0.596

The results are applied to form the final model to select the portfolio of high-technology projects. As a result, Table 13 presents the final results while assigning the weight 0.33 to Ω_g.

Table 13. Optimal portfolio of high technology projects

	X1	*X2*	*X3*	*X4*	*X5*	Objective function
Selected projects	0	1	0	1	1	1.39
Project manager	0	4	0	2	5	
Results obtained by Goal Programming						
	X1	*X2*	*X3*	*X4*	*X5*	Objective function
Selected projects	0	1	0	1	0	1.05
Project manager	0	4	0	2	0	

The results of Table 13 present the final portfolio of projects obtained by the multi-objective decision-making process applied in this study and goal programming. The results show that the presented method enhances the value of the objective function. The results are the same for projects *X2* and *X4*, but the comparison demonstrates the advantage of the applied optimization process by virtue of identifying project *X5* as an additional selection option.

In order to carry out a sensitivity analysis in the mathematical programming part of the approach, this section presents a sensitivity analysis based on various weights assigned to each objective (Ω_g). Table 14 presents the results.

Table 14. Optimal portfolio of high-technology projects

(Ω_1=0.25, Ω_2=0.25, Ω_3=5)	*X1*	*X2*	*X3*	*X4*	*X5*	Objective function
Selected projects	0	1	0	1	1	1.39
Project manager	0	4	0	2	5	
(Ω_1=0.25, Ω_2=0.5, Ω_3=0.25)	*X1*	*X2*	*X3*	*X4*	*X5*	Objective function
Selected projects	0	1	0	1	1	1.394
Project manager	0	4	0	2	5	
(Ω_1=0.5, Ω_2=0.25, Ω_3=0.25)	*X1*	*X2*	*X3*	*X4*	*X5*	Objective function
Selected projects	0	1	0	1	1	1.42
Project manager	0	4	0	2	5	
(Ω_1=0.1, Ω_2=0.1, Ω_3=0.8)	*X1*	*X2*	*X3*	*X4*	*X5*	Objective function
Selected projects	0	1	0	1	0	1.397
Project manager	0	4	0	2	0	
(Ω_1=0.1, Ω_2=0.8, Ω_3=0.1)	*X1*	*X2*	*X3*	*X4*	*X5*	Objective function

Selected projects	0	1	0	1	1	1.374
Project manager	0	4	0	2	0	
(Ω_1=0.8, Ω_2=0.1, Ω_3=0.1)	*X1*	*X2*	*X3*	*X4*	*X5*	Objective function
Selected projects	0	1	0	1	0	1.491
Project manager	0	4	0	2	0	

Table 13 presents the results while assigning various levels of importance to each goal. The application of the method in this case study demonstrates that the approach is able to properly address project evaluation in addition to project portfolio selection. In this case study various high technology projects for the automation of port operations have been evaluated. The results are used to form a multi-objective model to identify the best portfolio of high technology projects. Sensitivity analysis in both parts of the approach shows that this method can be applied as the core decision support system for the entire class of large, high technology project portfolio optimization.

5.8 Case study implications

The primary goal of this case study is to demonstrate some of the key features and their implications when using the proposed IVPFS method for high technology project evaluation. The following is a summary of the key implications:

- IVPFS offers an effective format for realistic expressions of uncertainty. The approach successfully resolves the requirement of IFS to express the degree of membership, non-membership and hesitancy within an overall set value that cannot exceed a value of 1. By employing IVPFS, expert opinion can now be addressed through a more practical condition, $0 \leq \left(\mu_C(x)\right)^2 + \left(\nu_C(x)\right)^2 \leq 1$. This permits the experts to focus more clearly on accurate expressions of both agreement and disagreement as independent variables.
- Aggregation is a vital step in any group decision-making process. Aggregation generally results in the consolidation of expert opinions into a single value. Unlike many studies, the aggregation in this study is not applied first. Leaving the aggregation until last retains as much information as possible, for as long as possible, during the optimization process. This study presents a new aggregation method that is shown to further improve the method presented by Zavadaskas et al. (2014).
- The application of IVPFS shown in this study ensures that the final outcome of project evaluation and the project portfolio selection are clear and explicit, and can be tested using standard sensitivity analysis techniques. The first, more substantial stage of the method results in evaluation scores that provide an actual aggregated ranking score, with the addition of a crisper, discrete ranking. The second stage of the method identifies the optimum selection of projects for a portfolio, along with an optimum assignment of project managers to each of the projects. Sensitivity analysis can be carried out in both key stages of the method application. This results in the formation of portfolios under various conditions, which helps reduce the risk of unpleasant surprises common to many practical situations.
- Employing an approach that combines both multi-attribute decision-making and multi-objective decision-making, results in a method that addresses more of the characteristic features of high technology projects. In particular, this approach investigates both the

quantitative and qualitative features of such projects. Moreover, by addressing the relative importance of both evaluation criteria and the domain experts, the sensitivity of the method to key drivers of the decision-making process is considerably improved. Finally, the capacity to consider additional factors (in this case the assignment of project managers to projects, and the project resilience) enhances the process of project portfolio optimization.

6. Conclusions and further research directions

Large, high technology projects are at the forefront of organizational and market transformation internationally. Evaluating such projects and identifying the best project portfolio within given resource limitations is an important decision-making process. There is a demonstrable lack of effective tools and techniques to address the levels and forms of complexity and uncertainty that typically characterize such projects. This study proposes a new approach to high technology project portfolio optimization and evaluation. The project evaluation adopts a last aggregation approach, with novel extensions of techniques used to weight both the domain experts and the evaluation criteria. A new form of linear assignment interval-valued Pythagorean fuzzy sets is applied to improve the evaluation process and specifically address the higher levels of uncertainty associated with large, high technology projects. A novel multi-objective model is then introduced to address project portfolio selection while optimizing the value of the portfolio in terms of resilience (risk of disruption and delays) and skill utilization (project manager assignment). The proposed model was applied to evaluate a specific case of high technology automation projects in port operations, and a comprehensive sensitivity analysis is presented.

The developed method has several key advantages over previous approaches, as demonstrated in the case study application presented in this study. First, the flexibility of the approach has been enhanced by separating the two main stages. This separation has allowed a variety of tools and techniques to be included and the advantages of each to be leveraged. Second, the capacity of the IVPFS approach to deal with a broader range and richer expression of uncertainty greatly improves how the uncertain nature of high technology can be addressed. Third, providing a last aggregation gives the approach the ability to employ all of the available data and to avoid the informational loss associated with any form of aggregation until the very end of the process. Fourth, the twofold weighting of the domain experts and the decision-making criteria greatly enhanced the outcome of the decision-making process by addressing practical and abiding aspects of the high technology decision-making problem. Fifth, the practicality and flexibility of the approach is demonstrated by considering additional factors such as the assignment of project managers, and the resilience of the portfolio selection to common risks of disruption and delay.

Some particularly challenging issues arose during the development of this study, and are referenced here as possible requirements for further studies:

- The novel approach presented in this study incorporates a number of relatively complicated and potentially time-consuming steps needed to resolve the case study effectively. There is ample scope to automate many of the steps and improve the transparency of each step, and either outcome would greatly assist in the development of a more practical application of the approach.

- This study has developed the IVPFS approach as an effective means to address the uncertainty in large, high technology projects. However, the treatment of uncertainty could be further enhanced by the introduction of a fuzzy stochastic uncertainty analysis. Given the nature of the uncertainty in high technology project decision-making, the use of fuzzy stochastic uncertainty would improve the capacity of the approach to deal with real project contexts.
- Multiple criteria have been included in the evaluation process of this case study. The actual criteria are representative criteria for the particular case study, but representative only. Their purpose is to demonstrate the capacity of the technique. For results that are more realistic in a practical case study of high technology projects, a more systematic literature review of the required evaluation criteria would be required in association with a more formal knowledge mining process specific to the particular client.
- The flexibility of the approach also warrants further study. The particular tools and techniques included in this case study, including linear assignment method, knowledge index, expert weighting, weighted aggregation method, and multi-objective decision-making tools, are only a particular selection of the many comparable tools and techniques available. The developed framework is capable of accommodating many additional and alternative tools and techniques, which makes the approach especially important for future research studies. Alternative combinations of tools and techniques within the developed framework could be applied to a variety of problem domains. The framework also has potential as the vehicle for a comprehensive comparative evaluation of all the candidate tools and techniques available for this class of decision-making problem.

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