Introducing a multi-criteria evaluation method using Pythagorean fuzzy sets: A case study focusing on resilient construction project selection

Abstract

Purpose - Project selection is a critical decision for any organization seeking to commission a large-scale construction project. Project selection is a complex multi-criteria decision-making problem with significant uncertainty and high risks. Fuzzy set theory has been used to address various aspects of project uncertainty, but with key practical limitations. This study develops and applies a novel Pythagorean fuzzy sets (PFSs) approach that overcomes these key limitations.

Design/methodology/approach – The study is particular to complex project selection in the context of increasing interest in resilience as a key project selection criterion. Project resilience is proposed and considered in the specific situation of a large-scale construction project selection case study. The case study develops and applies a Pythagorean fuzzy set (PFS) approach to manage project uncertainty. The case study is presented to demonstrate how PFS is applied to a practical problem of realistic complexity. Working through the case study highlights some of the key benefits of the PFS approach for practicing project managers and decision-makers in general.

Finding – The Pythagorean fuzzy sets (PFSs) approach proposed in this study is shown to be scalable, efficient, generalizable and practical. The results confirm that the inclusion of last aggregation and last defuzzification avoids the potentially critical information loss and relative lack of transparency. Most especially, the developed PFS is able to accommodate and manage domain expert expressions of uncertainty that are realistic and practical.

Originality/value – The main novelty of this study is to address project resilience in form of multi-criteria evaluation and decision making under PFS uncertainty. The approach is defined mathematically and presented as a six-step approach to decision making. The PFS approach is shown to allow multiple domain experts to focus more clearly on accurate expressions of their agreement and disagreement. PFS is shown to be an important new direction in practical multi-criteria decision-making methods for the project management practitioner.

Keywords: Construction project selection, project resilience, Pythagorean fuzzy sets (PFS), large-scale road construction, uncertainty.

1. Introduction

Large-scale construction projects are uncertain propositions: disruptions and changes are common, and these typically impede the contractor in completing the project on time, on budget and/or to the level of quality required (Eden et al., 2000; Marzoughi et al., 2018; Davoudabadi et al., 2019). Project resilience is then a measure for how effectively the contractor is able to respond to and overcome the impact of a disruptive event. Resilience in this sense is a function of factors such as the contractor flexibility, responsiveness, quality, productivity and accessibility (Rajesh, 2016). More recent definitions of resilience continue to broaden the concept beyond merely the effective survival of disruptions, to also require some outcome improvement from the disruptive event (Rajesh, 2016; Wieland and Marcus Wallenburg, 2013; Brandon-Jones et al., 2014; Scholten et al., 2014). For example, the rate of recovery and the capacity to build back better following a disruption have both been proposed as fundamentally important aspects of resilience (Mojtahedi et al., 2017). Given the broader definition, resilience is gaining increasing traction as a key performance indicator for large-scale construction project success. With the growing propensity for more project-driven organizations in general, resilience is also set to become a key performance indicator for organizations more broadly.

Any key performance indicator of success also warrants being a key factor in risk management. Where delays, disruptions and project complexity have been the major risk management issues to date (Bordoli and Baldwin, 1998), resilience must now also be included. A consideration of resilience in the risk management context also offers new opportunities to address some of the abiding problems facing risk management practice, specifically for this study: dealing with uncertainty (Talet et al., 2014). Uncertainty in risk management is about variability and ambiguity (Chapman et al., 2006). Variability refers to when a measurable factor can take on a range of possible values. Ambiguity refers to a range of potential meanings or interpretations of what constitutes each factor. Whilst risk arises from uncertainty, risk and uncertainty are not theoretically synonymous. Risk and uncertainty may represent a continuum between the two concepts with perhaps the greatest risk management challenges at the uncertainty end of the spectrum (Harvett, 2013).

The expanded concept of resilience provides a key mechanism by which an organization can move from reactive to proactive risk management (Hollnagel et al., 2007). Resilience in this case is defined and explained from two main levels of consideration: strategic and operational (Winnard et al., 2014; Winnard et al., 2016; Winnard et al., 2018). Strategic resilience is the ability to dynamically adjust and remodel business plans and the operational environment, and favors diversification. Operational resilience focusses on project delivery and optimizing within relatively constant conditions, and favors specialization (Hamel and Välikangas, 2003). In other words, strategic resilience is more concerned with effectiveness and decision-making while operational resilience is concerned with efficiency. This paper aims to improve strategic resilience through more effective decision-making in project selection using a multi-criteria framework.

To assess the resilience of a project it is necessary to identify the representative range of criteria associated with project resilience. Indicators such as flexibility, complexity, responsiveness, culture, accessibility, and buffering capacity have all been proposed to assess project resilience (Eikeland, 1998; Dehlin, 2008; Thomas et al., 2002; Woods, 2003). Flexibility measures the number of alternative options available to deal with disruptive events, and indicates resilience level of robustness (Mandelbaum and Buzacott, 1990; Eikeland, 1998; Zhang et al., 2019). Complexity is a measure of intractability or how obscure the internal dynamics (or 'true nature') of a project might be (Dehlin, 2008). Consequently, complexity adds to uncertainty and weakens project resilience. Responsiveness is broadly a measure of stakeholder engagement. Resilience will tend to improve as projects become more responsive to stakeholder requirements and concerns. The culture of a project is a measure of how the project or organization is structured to provide the required transparency with which disruptive events can be identified, uncertainty can be acknowledged, information accessed, and so on (Thomas et al., 2002). Accessibility measures the availability of a wide range of resources, information, technology, etc., each of which can help improve the ability of a project or organization to deal with disruptions and unwanted events. Buffering capacity is a measure of the amount of disruption that a project or organization can absorb before its performance begins to fail (Woods, 2003). For each of these criteria an absolute measure is problematic, and the critical methodological issue is how to deal with the uncertainty inherent in the measure (Mohagheghi et al., 2016; Mavrotas and Pechak, 2013). Furthermore, decision makers are often challenged with a lack of information about the extent and nature of the inherent uncertainty, along with inadequate training or expertise in the calculation and/or interpretion of the uncertainty measures (Hsu, 2014).

Fuzzy set theory is used extensively to address various aspects of project uncertainty (see for example, Mousavi et al., 2015; Mohagheghi et al., 2017b). Fuzzy sets have been used to address project cash flow assessment given uncertainty in the task durations and costs (Maravas and Pantouvakis, 2012), and earned value management in project management (Naeni et al., 2014). Fuzzy multi-criteria decision-making has been applied to assess overall project risk (Kuo and Lu, 2013). The fuzzy analytic hierarchy process has been used to assess the complexity of transportation projects (Nguyen et al., 2015), and with goal programming to manage the location and relocation of projects (Trivedi and Singh, 2017). Thuong et al. (2018) applied financial statement quality using a multi-criteria group evaluation method, which concurrently considered the quantitative examinations and qualitative opinions of evaluators. Their method employed hesitant fuzzy judgment description with an embedded assessing attitude. Al-Refaie et al. (2019) introduced an approach to optimize performance of manufacturing processes for multiple quality responses using a fuzzy goal programming-regression approach. Their approach in comparison with the Taguchi method, artificial neural networks, fuzzy regression, and grey-Taguchi method provided larger anticipated improvement in quality responses, efficiently deals with fuzziness and irregular process performance. Pramanik et al. (2019) established an intelligent model by integrating fuzzy Shannon entropy and fuzzy technique for order preference by similarity to ideal solution method (FTOPSIS) techniques as a decision tool for solving MCDM problem using linguistic values. Despite positive contributions and important capabilities however, classic fuzzy set theory has several critical limitations (Zimmermann, 2010). The particular limitation of concern in this study is the requirement for a decision maker or domain expert to express an exact opinion of uncertainty within the number interval [0, 1] (Mohagheghi et al., 2015a,b).

The development of an intuitionistic fuzzy set (IFS) is one response to the limitation of classic fuzzy set theory with regard to exact opinions. An IFS represents set membership, non-membership and confidence by degree through the application of a grade of membership function for each case. In addition to the fuzziness of the membership an IFS can also address a difference of opinion between decision-makers (Szmidt et al., 2014; Xu and Liao, 2014). Notwithstanding the extent to which IFS has been applied successfully in the large-scale construction project context, the approach has identified limitations of its own (Peng and Yang, 2015; Zhang and Xu, 2014; Mohagheghi et al., 2017a). To address the shortcomings, an extension of IFS has been developed by Yager (2013, 2014). The Pythagorean fuzzy set (PFS) provides more powerful, flexible and ultimately more practical expressions of membership functions by decision-makers. Despite the enhanced capability of PFS over IFS, the method is yet to be applied in a construction project risk management context. This study introduces PFS as a new method of evaluation for project resilience in the context of large-scale construction project risk management.

The PFS is proposed as part of a composite approach based around two established methods for multi-criteria decision making under uncertainty: MOORA (multi-objective optimization on the basis of ratio analysis) (Stanujkic et al., 2012; Medineckiene et al., 2015); and WASPAS (weighted aggregated sum product assessment) (Chakraborty et al., 2015). MOORA is a hybrid multi-criteria decision making method developed from well-established processes including TOPSIS (Hwang et al., 1993). This method has added functionality to make the method more efficient and easier to use (Stanujkic et al., 2012). The MOORA method has been applied in several studies to address decision-making problems. For instance, Akkaya et al. (2015) applied the MOORA to address industrial engineering sector selection. A fuzzy MOORA method was integrated with FMEA (Failure mode and effects analysis) to present a method for sustainable supplier selection (Arabsheybani et al., 2018). Dinçer et al. (2019) presented an integrated method by using the MOORA, DEMATEL and ANP to evaluated financial services. The MOORA method has been also applied to address project-related problems such as: project critical path selection (Dorfeshan et al., 2018); construction project manager selection (Ugur, 2017); and combined with mathematical programming, the portfolio selection of high technology projects (Mohagheghi and Mousavi, 2019).

MOORA depends on the aggregation as the last step, which also reduces the information loss significantly. WASPAS is used to ensure the highest accuracy of estimation is obtained at that stage by optimizing the weighted aggregated function. WASPAS is preferred over other available methods because it improves the accuracy of the ranking process (Zavadskas et al., 2014). WASPAS has been shown to be effective in a variety of applications. For example, Baušys and Juodagalvienė, (2017) used this approach to determine garage location selection for residential housing. Ghorabaee et al. (2017) have used the method to select a third-party logistics provider. Deveci et al. (2018) employed it to determine the location of a car-sharing station. Of particular relevance, Badalpur and Nurbakhsh (2019) proposed a method using WASPAS for the risk analysis of road construction projects.

To enhance the applicability of the approach under conditions of significant uncertainty, the notion of entropy is introduced to the expression of criteria weights. Entropy is a powerful concept for the measurement of uncertain information (Ye, 2010). In order to maintain the fuzziness of the overall decision-making process, the so-called ‘defuzzification step’ is also carried out in the latter stages of the process. Thus, the aim of this study is to enhance construction project decision-making by specifically addressing project resilience. This is done by using a multi-criteria evaluation approach that provides a flexible and practical method for dealing with the uncertainty characteristic of large-scale construction projects. Table 1 presents an overview of the literature as it relates to the key issues raised in the context to this study. This further illustrates the novelty of the approach taken in this study.

Table 1. Comparison of related construction decision-making studies with the current study

	Criteria	Process			Uncertainty			
	Resilience	MCDM in construction	Last aggregation	Defuzzification	Using fuzzy sets	Addressing disagreement	Addressing hesitancy	Using PFS
Tayan et al. (2014)		*			*			
Ravanshadnia et al. (2010)		*			*			
Ebrahimnejad et al. (2011)		*			*			
Tan et al. (2010)		*			*			
Rejment and Dziadosz (2014)		*						
Karakhan et al. (2018)		*						
Zolfani et al. (2018)		*						
Hatefi and Tamošaitienė (2018)		*			*			
This study	*	*	*	*	*	*	*	*

This study comprises the following key elements:

- The concept of project resilience is defined in terms of the evaluation process.
- Key project resilience factors are introduced.
- The PFS approach is used to address project uncertainty.
- The ratio system of MOORA is extended and applied to a PFS.
- WASPAS is used to aggregate the rankings of project experts.
- To avoid information loss and express the importance of each project expert opinion, the judgments of the project experts are not aggregated until late in the process.
- To maintain the fuzziness of the project data caused by uncertainty, most of the computation is carried out under uncertainty and the defuzzification step is delayed to the latter stages.
- To demonstrate the applicability of the approach in practice, a case study is presented for the selection of large-scale construction projects.

The remainder of this paper is organized as follows: Section 2 outlines the preliminary development of a PFS approach; Section 3 develops the approach more specifically to evaluate project resilience; Section 4 then applies the method to a large-scale construction project case study; and Section 5 considers the implications of this approach for project managers. Finally, the paper is concluded in Section 6.

2. Preliminary development

A basic definition of IFS and PFS is presented as follows:

An IFS set like *C* in a universe of discourse (*X*) is presented as:

$$C = \{< x, \mu_C(x), \nu_C(x) > | x \in X\} \tag{1}$$

In the aforementioned Eq., $\mu_C : X \to [0,1]$ indicates the membership degree while $\nu_C : X \to [0,1]$ shows the degree of non-membership of element $x \in X$ to the set C, respectively. It should be noted that these values are considered under the following condition:

$$0 \leq \mu_c(x) + \nu_c(x) \leq 1 \tag{2}$$

Finally, these sets have a degree of indeterminacy $\pi_c(x)$ which is presented as follows:

$$\pi_c(x) = 1 - \mu_c(x) - \nu_c(x) \tag{3}$$

These sets were introduced by Atanassov (1983) and unlike classic fuzzy sets these sets have the significant advantage in the current context of allowing experts to express the degree of membership, non-membership and hesitancy. However, there are conditions that these sets are unable to address. One of these conditions is when the sum of the degree that an alternative such as x_i both satisfies and dissatisfies with respect to attribute L_j is bigger than 1. In other words, a situation in which the degrees of membership and non-membership add up to values that are not limited to 1. It is apparent from the foregoing equations that such a condition cannot be expressed by IFS. To overcome this issue, Yager (2013, 2014) developed the concept of PFS.

A PFS (C) in a universe of discourse (X) is denoted as:

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

Where, $\mu_C : X \to [0,1]$ indicates the membership degree while $\nu_C : X \to [0,1]$ shows the degree of non-membership of element $x \in X$ to the set C, respectively. It should be noted that these values are considered under the following condition:

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

Consequently, the degree of indeterminacy $\pi_C(x)$ will be presented as follows:

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

Zhang and Xu (2014) referred to $\left(\mu_C(x), \nu_C(x)\right)$ as a Pythagorean fuzzy number (PFN) displayed by C=(μ_C, ν_C).

The main difference between PFN and an intuitionist fuzzy number (IFN) is in their constraint condition. Figure 1 provides an illustrative comparison of IFNs and PFNs based on the study of Peng and Yang (2015).

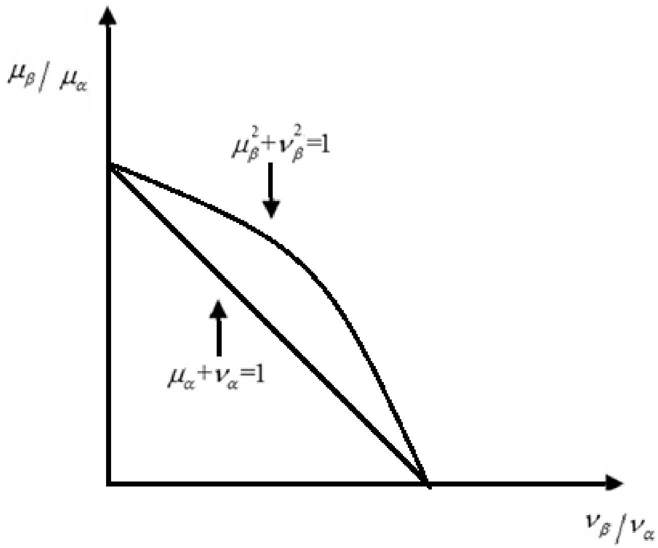

Figure 1. Comparison of IFNs and PFNs

Let $p_1 = (\mu_1, \nu_1)$ and $p_1 = (\mu_1, \nu_1)$ be two PFNs and $\rho > 0$. The following operations are presented for PFNs (Zhang and Xu, 2014; Peng and Yang, 2015):

$$p_1 \oplus p_2 = \left(\sqrt{\mu_1^2 + \mu_2^2 - \mu_1^2\mu_2^2}, \upsilon_1\upsilon_2\right); \tag{7}$$

$$p_1 \otimes p_2 = \left(\mu_1\mu_2, \sqrt{\upsilon_1^2 + \upsilon_2^2 - \upsilon_1^2\upsilon_2^2}\right); \tag{8}$$

$$\rho p_1 = \left(\sqrt{1 - (1 - (\mu_1)^2)^\rho}, (\upsilon_1)^\rho\right) \tag{9}$$

$$p_1 \ominus p_2 = \left(\sqrt{\frac{\mu_1^2 - \mu_2^2}{1 - \mu_2^2}}, \frac{\upsilon_1}{\upsilon_2}\right), if\ \mu_1 \geq \mu_2, \nu_1 \leq min\left\{\nu_2, \frac{\nu_2.\pi_1}{\pi_2}\right\} \tag{10}$$

$$\frac{p_1}{p_2} = \left(\frac{\mu_1}{\mu_2}, \sqrt{\frac{\upsilon_1^2 - \upsilon_2^2}{1 - \upsilon_2^2}}\right), if\ \mu_1 \leq min\left\{\mu_2, \frac{\mu_2.\pi_1}{\pi_2}\right\}, \nu_1 \geq \nu_2 \tag{11}$$

The distance between $p_1 and\ p_2$ is defined as follows (Zhang and Xu, 2014):

$$d(p_1, p_2) = \frac{1}{2}\left(\left|\left(\mu_{p_1}\right)^2 - \left(\mu_{p_2}\right)^2\right| + \left|\left(\nu_{p_1}\right)^2 - \left(\nu_{p_2}\right)^2\right| + \left|\left(\pi_{p_1}\right)^2 - \left(\pi_{p_2}\right)^2\right|\right) \tag{12}$$

The score function introduced by Zhang (2016) is used to present a crisp value of PFSs. Score function is presented as follows:

$$s(\beta) = \left(\mu_\beta\right)^2 - \left(\vartheta_\beta\right)^2 \tag{13}$$

3. Proposed methodology

In this section, a new method of project environment decision making under PFS uncertainty is introduced. The method has the following processes: the judgments of project experts are harvested and normalized. after normalization, the PFS ratio system of MOORA is computed. since the fuzziness of data is saved in this step, after calculating the ratio system PFS values are converted into comparable values. This is done through a new PFS ranking method. The flowchart of the proposed method is presented in Figure 2.

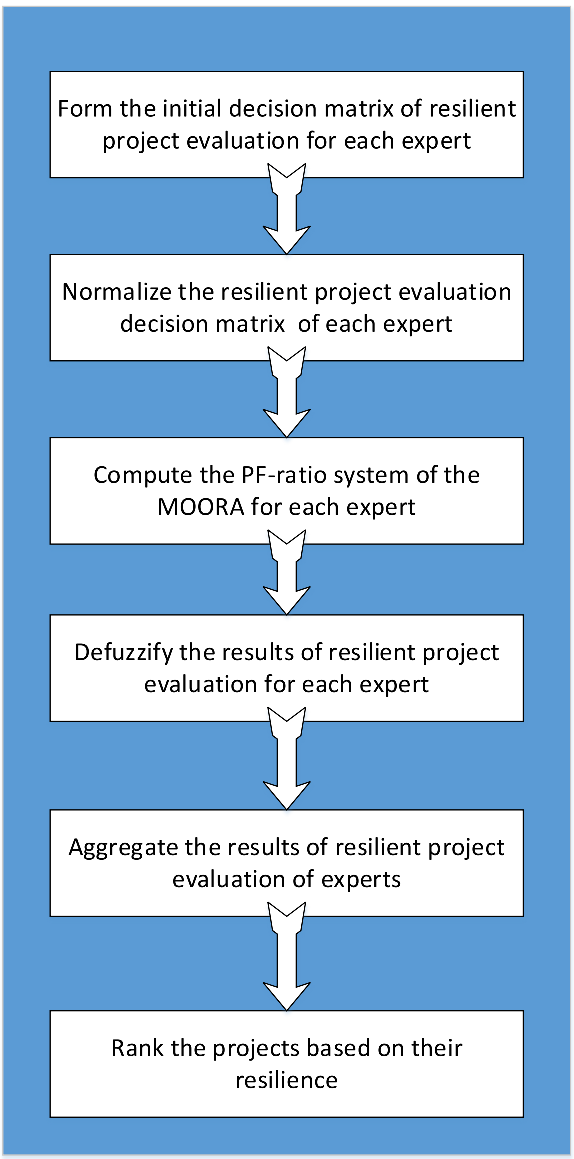

Figure 2. The flowchart of the proposed method

The step by step algorithm is presented as follows:

STEP 1.

The judgments of each project expert is gathered to form the initial decision matrices. As a result, the following expressions are made:

$$\widetilde{D}_k = \left(\widetilde{D}_{ij}^K\right)_{m\times n} = \begin{bmatrix} d(\mu_{11}^K, \nu_{11}^K) & \cdots & d(\mu_{1n}^K, \nu_{1n}^K) \\ \vdots & \ddots & \vdots \\ d(\mu_{m1}^K, \nu_{m1}^K) & \cdots & d(\mu_{mn}^K, \nu_{mn}^K) \end{bmatrix} \tag{14}$$

$$\widetilde{w}_j^k = (w(\mu_1^K, \nu_1^K), w(\mu_2^K, \nu_2^K), \dots, w(\mu_n^K, \nu_n^K)), K \in T \tag{15}$$

Where $\widetilde{D}_K$ shows the decision matrix for *k*th expert and $\widetilde{W}_K$ shows the weight of resilience assessment criteria according to the *k*th expert, n denotes the number of resilience assessment criteria, m shows number of compared projects and *T* denotes the group of project experts. Given the fact that this method is last aggregation, for each expert, a separate decision matrix is formulated and maintained. This is unlike the common first aggregation decision-making methods. In those methods the separate decision matrices are aggregated at this first step of the process, and the remainder of the process is then carried out using a single aggregated matrix. On the contrary, last aggregation maintains the discrete decision matrices until the latter stages, and thereby avoids any loss of information, making it the preferred method.

STEP 2.

Based on the study of Zhang and Xu (2014), the normalized decision matrix ($\widetilde{ND}$) can be computed by the means of the following:

$$\widetilde{ND}_{ij} = \begin{cases} d(\mu_{ij}^K, \nu_{ij}^K) \; for\ benefit\ criterion\ B_j \\ \left(d(\mu_{ij}^K, \nu_{ij}^K)\right)^c \; for\ cost\ criterion\ C_j \end{cases} \tag{16}$$

Where, $\left(d(\mu_{ij}^K, \nu_{ij}^K)\right)^c$ is the complement of $d(\mu_{ij}^K, \nu_{ij}^K)$ and is equal to $d(\nu_{ij}^K, \mu_{ij}^K)$ (Zhang and Xu, 2014). Also, $\widetilde{ND}$ denotes the normalized matrix. Normalization is required to ensure all criteria are compatible. In practice, two forms of criteria are possible. For example, cost and benefit criteria should, by nature, have opposite impacts on the objective as their respective values increase. Higher values for benefit criteria indicate improved conditions, whereas higher values for cost criteria indicate the opposite situation. Normailzation is performed in this step to guarantee that all criteria are compatible in relationship to the objective.

STEP 3.

MOORA method can be positioned conceptually between the SAW method (simple additive weighting) and the TOPSIS method (technique for order preference by similarity to an ideal solution). This positioning highlights the efficiency of this method. Moreover, this method is easy to use (Stanujkic et al., 2012). To use the advantages of the MOORA method in this study, at this stage of the decision-making process a new approach based on the concept of ratio system in MOORA and PFS is developed. The novel development of this method is presented as follows:

$$S_{iB}^{k} = \sum_{j\in B}\left(\mu\left(w_j^k\right).\mu\left(nd_{ij}^k\right), \sqrt{\nu(w_j^k)^2 + \nu(nd_{ij}^k)^2 - \nu(w_j^k)^2\nu(nd_{ij}^k)^2}\right) \tag{17}$$

$$S_{iC}^{k} = \sum_{j\in C}\left(\mu\left(w_j^k\right).\mu\left(nd_{ij}^k\right), \sqrt{\nu(w_j^k)^2 + \nu(nd_{ij}^k)^2 - \nu(w_j^k)^2\nu(nd_{ij}^k)^2}\right) \tag{18}$$

$$\begin{aligned} S_{i,Ratio\ system}^{k} = &\sum_{j\in B}\left(\mu\left(w_j^k\right).\mu\left(nd_{ij}^k\right), \sqrt{\nu(w_j^k)^2 + \nu(nd_{ij}^k)^2 - \nu(w_j^k)^2\nu(nd_{ij}^k)^2}\right) \\ &- \sum_{j\in C}\left(\mu\left(w_j^k\right).\mu\left(nd_{ij}^k\right), \sqrt{\nu(w_j^k)^2 + \nu(nd_{ij}^k)^2 - \nu(w_j^k)^2\nu(nd_{ij}^k)^2}\right) \end{aligned} \tag{19}$$

Where S_{iB}^{k} denotes the benefit score for each candidate project *i* in accordance to opinions of the *k*th expert. S_{iC}^{k} shows the cost score for each candidate project *i* in accordance to opinions of the *k*th expert. *B* denotes the set of benefit criteria. *C* denotes the set of cost criteria. $S_{i,Ratio\ system}^{k}$ denotes the overall score of each candidate project *i* in accordance to the opinions of *k*th expert.

STEP 4.

The outcome of Step 3 are values that denote how each candidate project reacts to each of the evaluation criteria. However, to maintain the fuzziness of the data in this process, fuzzy values are used to evaluate projects. In most of the similar methods, before the evaluation step a defuzzification step is carried out. That would result in crisp values denoting an evaluation score for each candidate project but has the disadvantage of losing the fuzziness of the data in the calculations. It is possible to postpone the defuzzification until a later step. Since fuzzy values are not easy to compare, this step presents a defuzzification and comparison method. In order to make the PFS values comparable, the following sub steps are applied:

4.1. Define the positive ideal solution as $S_{i,Ratio\ system,max}^{k}$ and the negative ideal solution as $S_{i,Ratio\ system,min}^{k}$ of *k*th expert for project *i* by using the concept of score function.

4.2. Calculate the distance based degree of similarity between each value of $S_{i,Ratio\ system}^{k}$and the positive ideal solution ($S_{i,Ratio\ system,max}^{k}$) for *i*th project according to the opinions of *k*th expert, denoted as d_i^{+k}, by applying Eq. (24):

$$\begin{aligned} d_i^{+k}&\left(S_{i,Ratio\ system}^{k}, S_{i,Ratio\ system,max}^{k}\right) \\ &= \frac{1}{2}\left(\left|\left(\mu_{s_i}^k\right)^2 - \left(\mu_{s_{i,max}}^k\right)^2\right| + \left|\left(\nu_{s_i}^k\right)^2 - \left(\nu_{s_{i,max}}^k\right)^2\right| + \left|\left(\pi_{s_i}^k\right)^2 - \left(\pi_{s_{i,max}}^k\right)^2\right|\right) \end{aligned} \tag{20}$$

4.3. Calculate the distance-based degree of similarity between each value of $S_{i,Ratio\ system}^{k}$and the negative ideal solution ($S_{i,Ratio\ system,min}^{k}$), denoted as d_i^{-k} for *i*th project according to the opinions of *k*th expert, by applying Eq. (25):

$$d_i^{-k}\left(S_{i,Ratio\ system}^k, S_{i,Ratio\ system,min}^k\right) = \frac{1}{2}\left(\left|\left(\mu_{s_i}^k\right)^2 - \left(\mu_{s_{i,min}}^k\right)^2\right| + \left|\left(\nu_{s_i}^k\right)^2 - \left(\nu_{s_{i,min}}^k\right)^2\right| + \left|\left(\pi_{s_i}^k\right)^2 - \left(\pi_{s_{i,min}}^k\right)^2\right|\right) \tag{21}$$

4.4. Determine the value of FR_i^k by using the following:

$$FR_i^k = \left(\frac{1}{2}\left(\left|\left(\mu_{s_i}^k\right)^2 - \left(\mu_{s_{i,min}}^k\right)^2\right| + \left|\left(\nu_{s_i}^k\right)^2 - \left(\nu_{s_{i,min}}^k\right)^2\right| + \left|\left(\pi_{s_i}^k\right)^2 - \left(\pi_{s_{i,min}}^k\right)^2\right|\right)\right) \times \left(\left(\frac{1}{2}\left(\left|\left(\mu_{s_i}^k\right)^2 - \left(\mu_{s_{i,min}}^k\right)^2\right| + \left|\left(\nu_{s_i}^k\right)^2 - \left(\nu_{s_{i,min}}^k\right)^2\right| + \left|\left(\pi_{s_i}^k\right)^2 - \left(\pi_{s_{i,min}}^k\right)^2\right|\right)\right) + \left(\frac{1}{2}\left(\left|\left(\mu_{s_i}^k\right)^2 - \left(\mu_{s_{i,max}}^k\right)^2\right| + \left|\left(\nu_{s_i}^k\right)^2 - \left(\nu_{s_{i,max}}^k\right)^2\right| + \left|\left(\pi_{s_i}^k\right)^2 - \left(\pi_{s_{i,max}}^k\right)^2\right|\right)\right)\right)^{1-}, i = 1,2,\dots,m \tag{22}$$

It should be noted that FR_i^k shows the final rating value of alternative *i* for *k*th expert.

STEP 5.

Use the following to aggregate the rankings of project experts and obtain the aggregated ranking score for project *i* (R_i):

$$
\begin{aligned}
R_i = \Bigg(\varphi \Bigg(\sum_{k=1}^{T} \Bigg(& \left(\frac{1}{2} \left(\left| \left(\mu_{s_i}^k\right)^2 - \left(\mu_{s_{i,min}}^k\right)^2 \right| + \left| \left(\nu_{s_i}^k\right)^2 - \left(\nu_{s_{i,min}}^k\right)^2 \right| + \left| \left(\pi_{s_i}^k\right)^2 - \left(\pi_{s_{i,min}}^k\right)^2 \right| \right) \right) \\
& \times \Bigg(\Bigg(\frac{1}{2} \left(\left| \left(\mu_{s_i}^k\right)^2 - \left(\mu_{s_{i,min}}^k\right)^2 \right| + \left| \left(\nu_{s_i}^k\right)^2 - \left(\nu_{s_{i,min}}^k\right)^2 \right| \right. \\
& \left. + \left| \left(\pi_{s_i}^k\right)^2 - \left(\pi_{s_{i,min}}^k\right)^2 \right| \right) \Bigg) \\
& + \Bigg(\frac{1}{2} \left(\left| \left(\mu_{s_i}^k\right)^2 - \left(\mu_{s_{i,max}}^k\right)^2 \right| + \left| \left(\nu_{s_i}^k\right)^2 - \left(\nu_{s_{i,max}}^k\right)^2 \right| \right. \\
& \left. + \left| \left(\pi_{s_i}^k\right)^2 - \left(\pi_{s_{i,max}}^k\right)^2 \right| \right) \Bigg) \Bigg)^{1-} \Bigg) WD_k \Bigg) \Bigg) \\
& + \Bigg((1 \\
& - \varphi) \prod_{k=1}^{T} \Bigg(\Bigg(\frac{1}{2} \left(\left| \left(\mu_{s_i}^k\right)^2 - \left(\mu_{s_{i,min}}^k\right)^2 \right| + \left| \left(\nu_{s_i}^k\right)^2 - \left(\nu_{s_{i,min}}^k\right)^2 \right| \right. \\
& \left. + \left| \left(\pi_{s_i}^k\right)^2 - \left(\pi_{s_{i,min}}^k\right)^2 \right| \right) \Bigg) \\
& \times \Bigg(\Bigg(\frac{1}{2} \left(\left| \left(\mu_{s_i}^k\right)^2 - \left(\mu_{s_{i,min}}^k\right)^2 \right| + \left| \left(\nu_{s_i}^k\right)^2 - \left(\nu_{s_{i,min}}^k\right)^2 \right| \right. \\
& \left. + \left| \left(\pi_{s_i}^k\right)^2 - \left(\pi_{s_{i,min}}^k\right)^2 \right| \right) \Bigg) \\
& + \Bigg(\frac{1}{2} \left(\left| \left(\mu_{s_i}^k\right)^2 - \left(\mu_{s_{i,max}}^k\right)^2 \right| + \left| \left(\nu_{s_i}^k\right)^2 - \left(\nu_{s_{i,max}}^k\right)^2 \right| \right. \\
& \left. + \left| \left(\pi_{s_i}^k\right)^2 - \left(\pi_{s_{i,max}}^k\right)^2 \right| \right) \Bigg) \Bigg)^{1-} \Bigg)^{WD_k} \Bigg)
\end{aligned}
\tag{23}
$$

Where WD_k is the weight of kth project expert and $0<\varphi<1$ denotes the importance of two approaches in aggregating the project expert rankings. It should be noted that $0<WD_k<1$ and $\sum_{k=1}^{K} WD_k = 1$. This aggregation is based on the WASPAS method, and retains the advantages of the WASPAS method in this process.

STEP 6.

Rank the alternative projects in decreasing order of R_i.

4. Large-scale construction project case study

4.1. Problem description

In order to demonstrate the applicability of the proposed method of project selection, a real-world case study is introduced. The case study considers a project-based organization with potential involvement in four, large-scale and high-profile national road construction projects (R_01, R_02, R_03, and R_04). Due to limited resources and broader strategic considerations, the company is keen to focus its bid on just a single project selected from the four. A critical factor is for the organization to promote its standing and reputation for the delivery of successful project outcomes, by selecting the project that is likely to be most resilient. Therefore it is facing the least risk of failure due to unforeseen events, disruptions and delays.

The four candidate road projects vary in their length of road, number of lanes required, annual operating capacity, construction period, fixed investment cost, climatic conditions, and geographic situation. The actual features for each of the proposed road projects are detailed in Table 2.

Table 2. Features of proposed freeway projects (Ministry of Road and Urban Development, 2015)

Project	R_01	R_02	R_03	R_04
Length of Road (km)	130	180	220	120
Number of Lanes	4	4	4	4 to 6
Operating Capacity (millions/year)	10	9	7	7
Construction Period (years)	3	4	3	2
Investment Cost (EUR million)	280	470	740	270
Climate Conditions	Arid Semi-Arid	Semi-Arid Cold	Semi-Arid	Arid Semi-Arid
Geography - Flats (%)	94	28	41	70
Geography - Hills (%)	6	36	13	19
Geography - Mountains (%)	0	36	46	11

The situation clearly warrants a multi-criteria decision-making approach. To establish the relative weighting for each criterion a panel of 3 domain experts (E_01, E_02, and E_03) was convened. Each of them had at least 10 years of experience in the project management of equivalent major road projects in this construction market for this particular organization. The expert opinion was sought using two questionnaires: one set of questions referred to the relative importance of each evaluation criterion; one set of questions referred to how each of the four projects performed against each criterion. For both sets of questions the experts were required to provide two numbers: one number expressed their degree of agreement $\mu_C(x)$; one number expressed their degree of disagreement $\nu_C(x)$. Along with each questionnaire a spreadsheet was provided to check that the relevant condition – $0 \leq (\mu_C(x))^2 + (\nu_C(x))^2 \leq 1$ – was satisfied and valid PFS values were submitted.

4.2. Criteria selection

In order to choose a set of criteria to assess the resilience of the projects, the method applied by Shaaban and Scheffran (2017) was adopted. In Figure 3, a visual presentation of the 6-step method applied to select the evaluation criteria is provided. As it is depicted in this figure, the process begins with a review of the related literature and interviews with domain experts. The literature review was undertaken to obtain a representative starting list of potential evaluation criteria. The focus of the literature review was on papers related to the subject of resilience (Birgani and Yazdandoost, 2018; Haldar et al., 2012; Hosseini et al., 2019; Omidvar et al., 2017; Parkouhi and Ghadikolaei, 2017; Kochan and Nowicki, 2018). The initial criteria list was then reviewed and supplemented by project manager domain experts. This step resulted in a comprehensive pool of potential evaluation criteria (step 2). In Step 3, for each potential criterion in the pool, an evaluation was undertaken to determine the frequency with which that criteria are identified in the related literature or by the domain experts. A cut-off threshold was used to exclude any criteria that was not referenced in at least 30% of the cases. In step 4, the reduced set of most frequently referenced criteria were then assessed following Shaaban and Scheffran (2017), using the following considerations:

1. Data availability – is it possible to source information on the criteria?

2. Consistency with the objective – is it possible to evaluate the resilience of the project to disruptive events?

3. Independence – are their interdependencies between criteria?

4. Measurability – how easy is it to measure the criteria in quantitative or qualitative terms?

5. Simplicity – will the criteria be understood by the domain experts in real-world applications?

6. Sensitivity – is it possible to undertake a trend analysis on the criteria?

7. Reliability – is it possible to incorporate both positive and negative aspects?

This step further concentrates the evaluation criteria. However, due to the subjective nature of many assessment considerations, in Step 5 questionnaires are used to finalize the set of most important evaluation criteria with the domain experts.

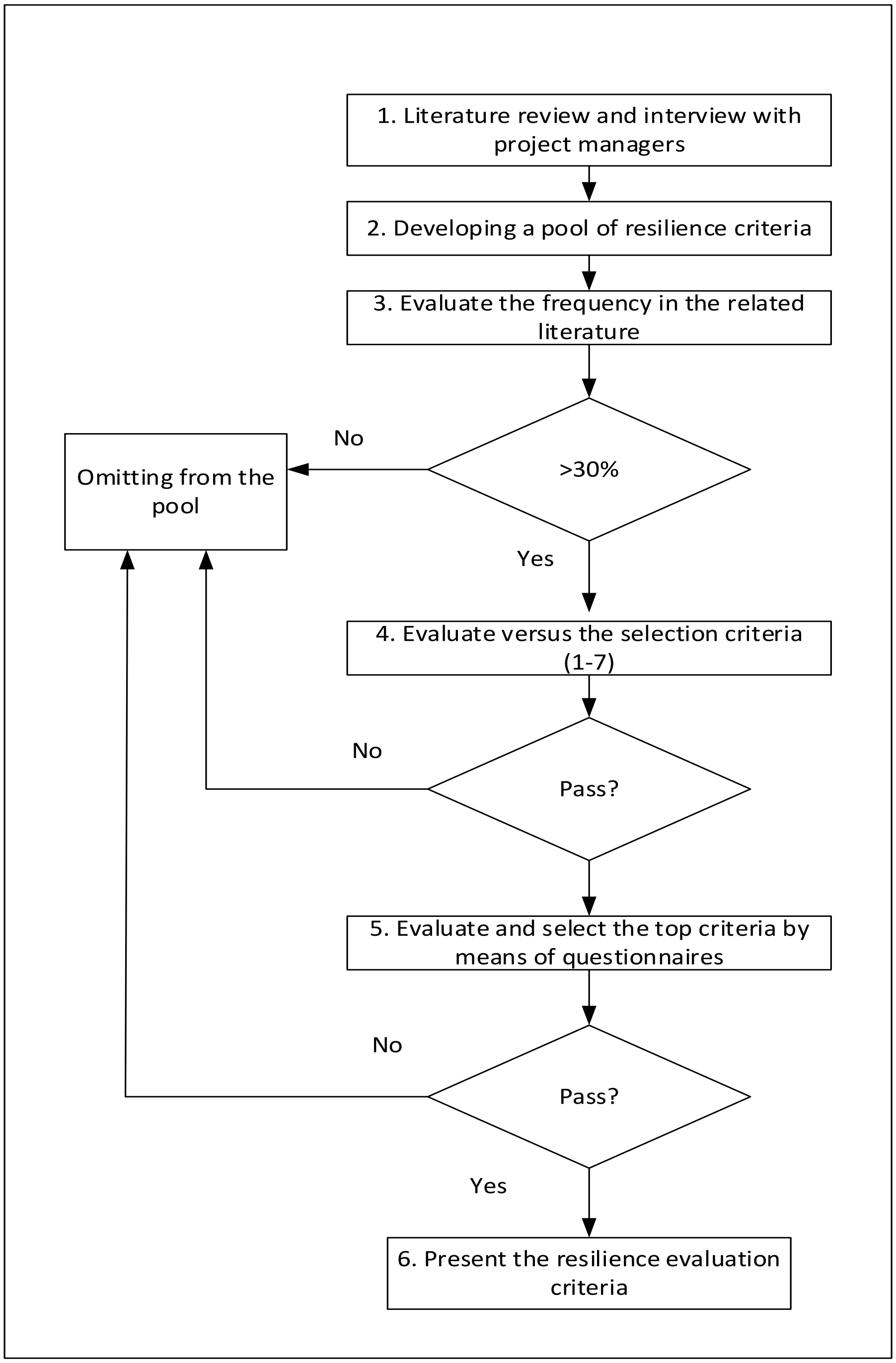

Figure 3. Resilience criteria selection process

At the conclusion of Step 5 the following resilience evaluation criteria were identified:

1. Project flexibility (C_01): is a measure of the capacity of a system to perform its function in the face of damage and changing context (Meepetchdee and Shah, 2007). Flexibility enhances the resilience of a system (Ishfaq, 2012).

2. Project complexity (C_02): is a feature that renders it increasingly difficult to comprehend, predict or control the overall behavior of a project, even when the information on the project is relatively complete (Vidal et al., 2011). An increase in project complexity results in a reduction in the level of resilience (Gunasekaran et al., 2015).

3. Buffer capacity (C_03): refers to the capacity of a project to accommodate project uncertainties (Goldratt, 1997). It is an intangible resource (Zhang et al., 2016). The greater the buffer capacity, the higher the level of resilience.

4. Stakeholder culture (C_04): is the extent to which resilience is a key consideration across all stakeholders and for all decisions (Seville, 2009; Mok et al., 2015). Stakeholders that actively support and promote project resilience, act to improve the resilience of those projects by prioritizing resilience in project decision-making.

5. Accessibility (C_05): indicates the extent to which activities in one location can access resources in another (Morris et al., 1979). Accessibility measures the availability of a wide range of resources, information, technology, etc., each of which can help improve the capacity of a project or organization to deal with disruptions and unwanted events. Accessibility improves resilience.

It is worth noting here that the project complexity (C_02) criterion is the only cost criteria (where a higher value detracts from the objective). All others in the list are benefit criteria (where a higher value improves the objective).

4.3. Evaluation process

Table 3 shows the results for the relative importance of each evaluation criterion as provided by the 3 domain experts. It can be noted that each domain expert assesses the relative importance of each evaluation criterion quite differently, and each evaluation criteria is assessed differently by each of the domain experts.

Table 3. Importance of each evaluation criterion

Expert	Flexibility (C_01)	Complexity (C_02)	Buffer (C_03)	Stakeholder (C_04)	Accessibility (C_05)
E_01	(0.8,0.2)	(0.7,0.4)	(0.6,0.5)	(0.6,0.4)	(0.6,0.5)
E_02	(0.8,0.4)	(0.8,0.3)	(0.7,0.4)	(0.8,0.3)	(0.7,0.4)
E_03	(0.9,0.2)	(0.9,0.3)	(0.5,0.5)	(0.6,0.3)	(0.5,0.5)

Table 4 shows the results for how each of the domain experts then rates each of the 4 projects against each of the 5 evaluation criteria. Again, it can be noted that the opportunity for domain experts to express an opinion on both membership and non-membership that does not necessarily sum to 1 results in ratings that vary in almost every case. This variation is a good signal that the introduction of the PFS approach is capturing meaningful and potentially significant information from the domain experts that would otherwise be excluded.

Table 4. Rating of each project versus evaluation criteria

Project	Expert	Flexibility (C_01)	Complexity (C_02)	Buffer (C_03)	Stakeholder (C_04)	Accessibility (C_05)
	E_01	(0.7,0.4)	(0.8,0.2)	(0.9,0.2)	(0.8,0.4)	(0.7,0.4)
	E_02	(0.8,0.3)	(0.8,0.3)	(0.9,0.4)	(0.8,0.5)	(0.9,0.3)
R_01	E_03	(0.9,0.3)	(0.7,0.5)	(0.8,0.3)	(0.7,0.4)	(0.7,0.3)
	E_01	(0.3,0.6)	(0.6,0.7)	(0.6,0.3)	(0.4,0.7)	(0.6,0.4)
	E_02	(0.3,0.7)	(0.5,0.2)	(0.4,0.6)	(0.5,0.5)	(0.4,0.8)
R_02	E_03	(0.5,0.5)	(0.5,0.5)	(0.3,0.7)	(0.3,0.8)	(0.4,0.9)
	E_01	(0.5,0.5)	(0.6,0.5)	(0.6,0.5)	(0.6,0.4)	(0.6,0.7)
	E_02	(0.6,0.5)	(0.55,0.4)	(0.5,0.5)	(0.6,0.5)	(0.6,0.5)
R_03	E_03	(0.6,0.5)	(0.6,0.45)	(0.4,0.5)	(0.7,0.5)	(0.5,0.5)
	E_01	(0.6,0.3)	(0.75,0.45)	(0.7,0.2)	(0.7,0.2)	(0.8,0.4)
	E_02	(0.7,0.4)	(0.6,0.4)	(0.5,0.7)	(0.6,0.3)	(0.75,0.35)
R_04	E_03	(0.6,0.5)	(0.8,0.6)	(0.5,0.5)	(0.8,0.4)	(0.7,0.2)

Following the proposed methodology, the judgments of project experts represented in Tables 3 and 4 are normalized using Equation 16. The normalized values are presented in Table 5. The agreement and disagreement values are now consistent in so far as the higher the value of the agreement column and the lower the value of the disagreement column, the better.

Table 5. The normalized project decision matrix

Project	Expert	Flexibility (C_01)	Complexity (C_02)	Buffer (C_03)	Stakeholder (C_04)	Accessibility (C_05)
	E_01	(0.7,0.4)	(0.2,0.8)	(0.9,0.2)	(0.8,0.4)	(0.7,0.4)
	E_02	(0.8,0.3)	(0.3,0.8)	(0.9,0.4)	(0.8,0.5)	(0.9,0.3)
R_01	E_03	(0.9,0.3)	(0.5,0.7)	(0.8,0.3)	(0.7,0.4)	(0.7,0.3)
	E_01	(0.3,0.6)	(0.7,0.6)	(0.6,0.3)	(0.4,0.7)	(0.6,0.4)
	E_02	(0.3,0.7)	(0.2,0.5)	(0.4,0.6)	(0.5,0.5)	(0.4,0.8)
R_02	E_03	(0.5,0.5)	(0.5,0.5)	(0.3,0.7)	(0.3,0.8)	(0.4,0.9)
	E_01	(0.5,0.5)	(0.5,0.6)	(0.6,0.5)	(0.6,0.4)	(0.6,0.7)
	E_02	(0.6,0.5)	(0.4,0.55)	(0.5,0.5)	(0.6,0.5)	(0.6,0.5)
R_03	E_03	(0.6,0.5)	(0.45,0.6)	(0.4,0.5)	(0.7,0.5)	(0.5,0.5)
	E_01	(0.6,0.3)	(0.45,0.75)	(0.7,0.2)	(0.7,0.2)	(0.8,0.4)
	E_02	(0.7,0.4)	(0.4,0.6)	(0.5,0.7)	(0.6,0.3)	(0.75,0.35)
R_04	E_03	(0.6,0.5)	(0.6,0.8)	(0.5,0.5)	(0.8,0.4)	(0.7,0.2)

The values presented in Table 6 are computed using Step 3 equations of the proposed method. Benefit criteria values represent S_{iB}^{k}, where the larger the value the more desirable the project. Cost criteria values represent S_{iC}^{k}, where the smaller the value the more desirable the project. The summation of benefit criteria and cost criteria are computed as values for the ratio system representing $S_{i,Ratio\ system}^{k}$, where the larger the value the more desirable the project. Because this method uses a last aggregation, the value for each expert is calculated separately.

Table 6. Results of the proposed method, Step 3

Project	Expert	Benefit Criteria	Cost Criteria	Ratio system
R_01	E_01	(0.99,0.012)	(0.2,0.8)	(0.99,0.01)
	E_02	(0.99,0.018)	(0.3,0.8)	(0.99,0.02)
	E_03	(0.99,0.010)	(0.5,0.7)	(0.98,0.015)
R_02	E_01	(0.82,0.05)	(0.7,0.6)	(0.62,0.08)
	E_02	(0.72,0.16)	(0.2,0.5)	(0.7,0.33)
	E_03	(0.69,0.25)	(0.5,0.5)	(0.55,0.50)
R_03	E_01	(0.89,0.07)	(0.5,0.6)	(0.85,0.11)
	E_02	(0.89,0.06)	(0.4,0.55)	(0.87,0.11)
	E_03	(0.89,0.06)	(0.45,0.6)	(0.86,0.1)
R_04	E_01	(0.96,0.004)	(0.45,0.75)	(0.96,0.006)
	E_02	(0.94,0.02)	(0.4,0.6)	(0.93,0.04)
	E_03	(0.95,0.02)	(0.6,0.8)	(0.92,0.02)

To achieve comparable values, the concept score function is used to calculate the ideal solution as $S_{i,Ratio\ system,max}^{k}$ and the negative ideal solution as $S_{i,Ratio\ system,min}^{k}$. Table 7 presents the results derived from Table 6 values. The maximum and minimum values presented are then applied in the defuzzification and comparison step.

Table 7. The values of $S_{i,Ratio\ system,max}^{k}$ and $S_{i,Ratio\ system,min}^{k}$

	$Maximum$	$Minimum$
E_01	(0.99,0.016)	(0.62,0.08)
E_02	(0.99,0.02)	(0.7,0.33)
E_03	(0.98,0.015)	(0.55,0.5)

Table 8 presents the values of d_i^{+k} and d_i^{-k}, which measure the difference between each candidate project and the respective maximum and minimum values shown in Table 7. The difference from the maximum represents the value of d_i^{+k} and is computed by using Equation 20. The difference from the minimum represents the value of d_i^{-k} and is computed by using Equation 21. The value of FR_i^k is obtained by using Equation 22 and provides a comparable score for each candidate project. The larger the value of the comparable score, the more desirable the project in resilience terms. Once again, given the last aggregation nature of this process, each calculation is determined separately for each project expert.

Table 8. The values of d_i^{+k}, d_i^{-k} and FR_i^k

Project	Expert	Difference to maximum	Difference to minimum	Comparable Score
R_01	E_01	0	0.3	1
	E_02	0	0.3	1
	E_03	0	0.46	1
R_02	E_01	0.3	0	0
	E_02	0.30	0	0
	E_03	0.46	0	0
R_03	E_01	0.13	0.17	0.58
	E_02	0.12	0.18	0.6
	E_03	0.12	0.34	0.73
R_04	E_01	0.2	0.27	0.9
	E_02	0.06	0.24	0.79
	E_03	0.05	0.4	0.87

To reach a final ranking of candidate projects it is necessary to aggregate the results across all experts. Aggregation can be carried out either early or late in the process. In the proposed method aggregation is carried out last. This keeps as much information as possible explicit in the calculations for as long as possible. Aggregation requires the individual scores from each domain expert to be weighted in some way. Weighting reflects the significance of each expert opinion in the ranking process. The proposed method allows for the weighting to be adjusted at this stage, which is important for sensitivity analysis and external control of the process. However, for the purposes of this case study the weightings are calculated as ɸ, based on the same arithmetic averaging of the values used in the WASPAS methodology.

Equation 23 is then applied to determine R_i, which represents the aggregated ranking score for each project. Based on the aggregated ranking score a discrete ranking of the projects can readily be determined. The higher the aggregated ranking score, the more desirable the project. Discrete ranking lists the most desirable project at number 1.

Table 9. The final ranking of projects

Project	Expert Weighting (E1, E2, E3)	Aggregated ranking score	Final Ranking	MOORA method (Pérez-Domínguez et al., 2018)		MOOSRA method (Adalı and Işık, 2017)	
				Score	Ranking	Score	Ranking
	(0.5,0.25,0.25)	1	1	1	1	1	1
	(0.25,0.5,0.25)	1	1				
R_01	(0.25,0.25,0.5)	1	1				
	(0.5,0.25,0.25)	0	4	0.02	4	0.04	4
	(0.25,0.5,0.25)	0	4				
R_02	(0.25,0.25,0.5)	0	4				
	(0.5,0.25,0.25)	0.625	3	0.43	3	0.86	3
	(0.25,0.5,0.25)	0.63	3				
R_03	(0.25,0.25,0.5)	0.66	3				
	(0.5,0.25,0.25)	0.87	2	0.74	2	0.9	2
	(0.25,0.5,0.25)	0.84	2				
R_04	(0.25,0.25,0.5)	0.86	2				

As detailed in Table 9, the preferred project in resilience terms is project R_01. It is a relatively clear preference based on the expert opinions of the 3 selected domain experts and the various conditions set for the evaluation. As with any such evaluation, sensitivity analysis and assumption testing should be used to determine the stability of this ranking under different scenarios. It is also the case that increasing the number of domain experts on whose opinions the ranking is based would add important statistical significance to the decision. There is minimal calculation overhead beyond the data collection stage to applying the proposed method to a larger pool of expert opinion. Further, the focus of this case study has been on resilience as the key evaluation criteria. Again however, there is little calculation overhead to extending the number of criteria used as the basis of the evaluation. The method is entirely scalable from a computational standpoint, although the more evaluation criteria used, the more opinions are required from each expert.

In order to validate the results and compare the results with other methods, the ratio systems of the MOORA method and the MOOSRA method are applied to rank the alternatives. The results are presented in Table 9. The results show that the presented method provides the same rank ordering results. However, the presented method has several novel points of improvement, including the use of last aggregation and defuzzifying the results in the final step.

Most importantly, the use of PFS in the proposed method has relaxed an important constraint on how the domain experts are able to express their degree of agreement and disagreement. The process of calculation is relatively straightforward and at every step the relative significance of each opinion, weighting and normalization is evident. Leaving aggregation until the very last stage adds considerably to the transparency of the evaluation method. This transparency lies in the fact that the process is carried out for each project expert; therefore, impacts of each expert in the process are visible and tractable.

4.4. Discussion of the process

In order to present the advantages of this model in addition to analyzing the results, this section offers discussion on the process. First, for comparison, the problem is also solved using a first aggregation process. Table 10 presents the comparative results of the first aggregation versus the last aggregation process. These results are presented graphically in Figure 4.

Table 10. Comparative results of the first versus the last aggregation process

	First aggregation		Last aggregation	
Project	Ranking Score	Final Ranking	Ranking Score	Final Ranking
R_01	1	1	1	1
R_02	0	4	0	4
R_03	0.51	3	0.64	3
R_04	0.84	2	0.86	2

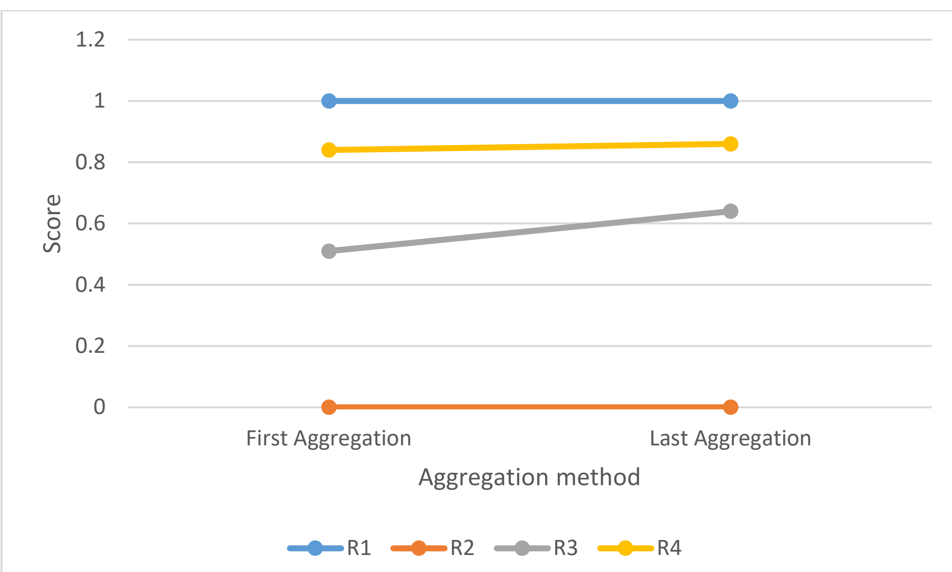

Figure 4. Comparison of the results in the first aggregation and the last aggregation processes

In order to equalize the comparison of the first versus the last aggregation process, weights of the experts in the aggregation step were initially considered equal. The results depicted in Table 10 and Figure 4 show that under those conditions the ranking has remained intact. However, the scores of the projects R3 and R4 have changed, meaning the final ranking could also change in other circumstances. Given that the first aggregation process aggregates in the initial steps and therefore results in a loss of information during subsequent stages, the last aggregation is to be preferred. The results given in this exercise confirm that the loss of information could be significant to the final ranking process under particular conditions.

Another advantage of the proposed last aggregation process is the possibility of analyzing the results based on variations in the weights assigned to the experts. In a group decision-making problem, experts are brought from various backgrounds with the intention that each bring a potentially different point of view to the consideration. Therefore, it is important to test the sensitivity of the outcomes to variations in the relative weightings of the experts. Analysis applying different levels of importance to the expert opinions are especially straight-forward with the last aggregation process as only the final step calculations need to be repeated, rather than the entire evaluation process required by first aggregation. The results of this sensitivity analysis under the current conditions using last aggregation are presented in Figure 5.

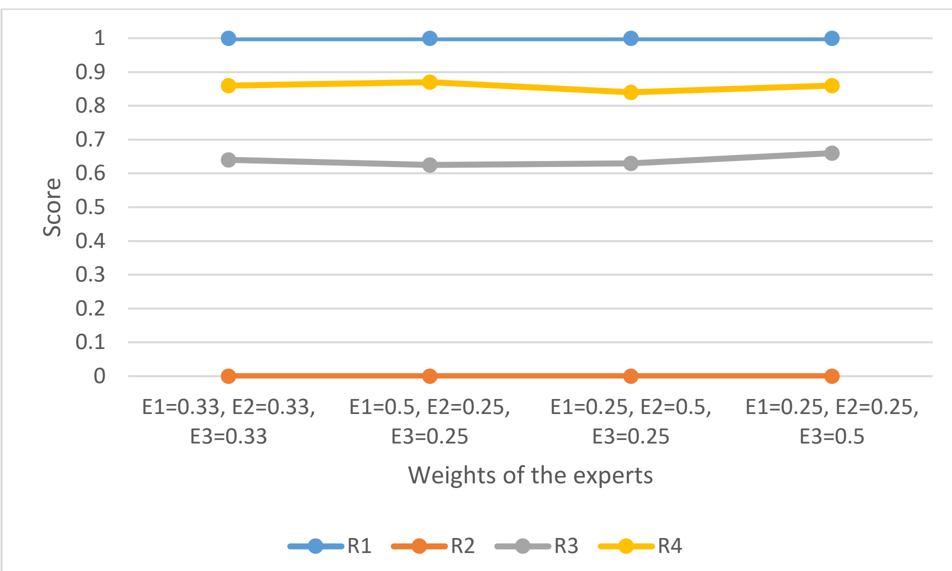

Figure 5. Comparison of the results in the last aggregation process with different weights for experts

Figure 5 presents the difference in the ranking scores for the alternative projects when the relative weighting or importance of the expert opinions is varied. The results indicate that results R3 and R4 are most sensitive to changes in the weighting given to the individual experts. This kind of presentation provides the key decision makers with a better understanding of how stable each alternative is under different assumptions regarding the relative importance of each expert opinion.

In a similar fashion to the first comparison between first and last aggregation, the second comparison is between initial and final stage defuzzification. For this comparison, the removal of the fuzziness from the expression of the data is undertaken at the start (as is common with current approaches) and the end of the process (as is proposed in the method developed in this study). Table 11 and Figure 6 present the results of the first and last defuzzification process comparison. It should be noted that the domain expert opinions were given equal weights in this comparison.

Table 11. The results using first and last defuzzification processes

	First defuzzification		Last defuzzification	
Project	Ranking Score	Final Ranking	Ranking Score	Final Ranking
R_01	1	1	1	1
R_02	0.02	4	0	4
R_03	0.39	3	0.64	3
R_04	0.69	2	0.86	2

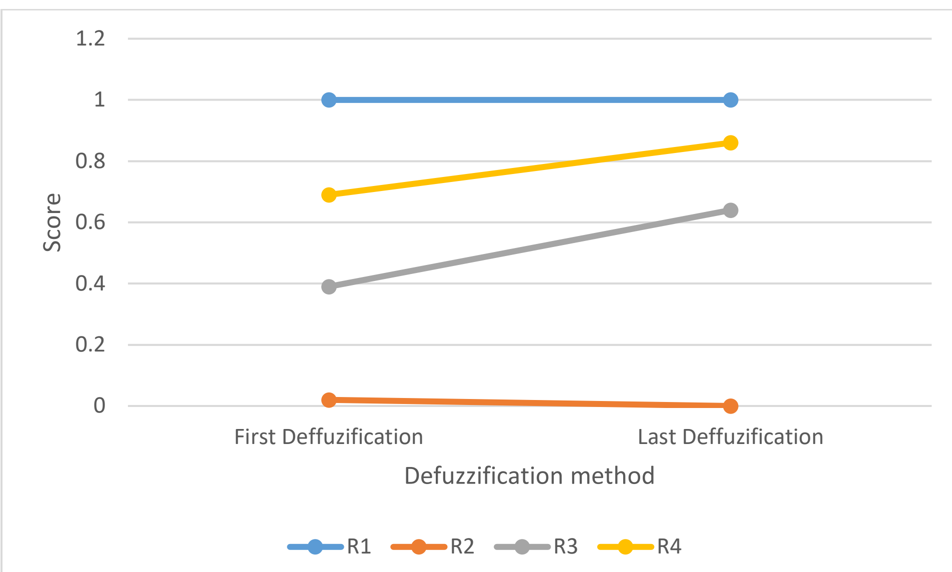

Figure 6. Comparison of the results between a first and last defuzzification process

The results depicted in Table 11 and Figure 6 shows that for the current case study, first and last defuzzification has no impact on the final rankings of the projects. There are however changes in the ranking scores between the two approaches that indicate the strong potential for final rankings to be affected in other circumstances. The fact that defuzzification in the early stages of a ranking process results in the majority of the computation being completed with crisp data, does undermine the concept of a fuzzy decision-making approach. The fact that there is such apparent differences between the two approaches signifies that retaining fuzzy expressions until late in the process does have a discernable impact on the outcomes. The last defuzzification process is to be preferred.

4.5. Discussion of the results

The results of the case study analysis show that project R_01 is preferred under all conditions considered. This is to be expected given the values expressed in Tables 3 and 4, wherein R_01 tended to be ranked relatively high by all 3 domain experts across all evaluation criteria. In particular, the most discernible difference in project rankings occurred against evaluation criteria C_01 (Flexibility) and C_02 (Complexity), both of which were also generally rated as the highest relative importance as evaluation criteria. One can note that this ranking reflects the general characteristics of project R_01, which is of relatively shorter duration and lower cost, and most especially constructed over a larger proportion of geographic flats. All of these factors point to a more straight forward (likely fewer bridges, fewer tunnels, less investment, faster return, etc.) and lower risk construction proposition.

Table 4 is also indicative of the variation in opinions and the degree of uncertainty faced when having to manage decision-making across multiple criteria and competing expert opinions in practice. In almost every case shown in Table 4, the membership and non-membership expressions by the individual experts is different across each of the evaluation criteria. This confirms the nature of practical multi-criteria decision-making processes particular to large-scale construction projects. This also strongly supports the use of fuzzy decision-making models in the process. Indeed, the sensitivity analyses undertaken support entirely the proposition that current fuzzy decision-making models are largely inadequate for practical decision-making tasks of this nature. The preponderance of combined membership and non-membership values that exceed 1 is also testament to the need for a PFS approach, as developed in this study.

The overall objective of this assessment case study is project resilience. It is a project objective of growing importance to organizations involved in large-scale construction projects. The variability in the performance of projects in this case study against this objective is testament to the need for a formal evaluation and sensitivity analysis process to be developed and applied in this regard. The independence and significance of the 5 key evaluation criteria is confirmed in this case study and the criteria identified can now be applied more generally to subsequent studies.

5. Implications for the project manager

The purpose of the case study is to demonstrate some of the key implications of the proposed evaluation method for practicing project managers. These implications are summarized as follows:

(i) Resilience is an important criterion to include in any complex project evaluation.

Disruption and delay are well-known as important factors in risk management. Increasingly, the project management literature is highlighting the significance of resilience as a means of dampening the potential impact of disruptive events. Most recently, resilience is also being considered a means to maximize the potential opportunity to improve processes going forward, by building back better. Project evaluation is already a complex multi-criteria decision-making problem, and adding a further criterion such as resilience will only compound that complexity further. However, without the inclusion of resilience as a principal criterion, any evaluation of project risk is susceptible to selecting at best a sub-optimum and at worst a failed project outcome. The added complexity is a necessary condition to yield more reliable outcomes. The PFS approach presented in this study is shown to accommodate a sufficient range of evaluation criteria, with sufficient transparency and flexibility to soundly inform the practicing project manager on the comparative performance of competing projects in resilience terms.

(ii) The proposed evaluation method provides a clear and simple process of calculation.

There is increasing use of multi-criteria decision-making techniques in combination with group decision-making techniques to accommodate the potential range of preferences of different stakeholders across different evaluation criteria (Diaz-Balteiro et al., 2017). In keeping with the criticisms of black-box methods in general (Cinelli et al., 2014), it is especially important that complex decision-making problems are addressed in a transparent and flexible process. The PFS approach presented in this study involves calculations that are relatively straight-forward for the project manager/decision-maker to compute and comprehend. The calculations are standard for a range of current modeling software used in business. The steps all result in meaningful representations of relevant data that the decision maker can interrogate further at each stage if required.

(iii) PFS offers an effective format for realistic expressions of uncertainty by domain experts.

The development of IFS and its increasing application in project management is testament to the limitations of classic fuzzy set theory and the strong appeal for a decision-making method that recognizes vague and potentially conflicting expert opinions. The PFS approach presented in this study takes a further step in recognizing the practical limitations of having to restrict the degree of membership, non-membership and confidence to an overall set value that does not exceed a value of 1. Expert opinion can now be canvassed and addressed provided only that the more practical condition – $0 \leq \left(\mu_C(x)\right)^2 + \left(\nu_C(x)\right)^2 \leq 1$ – is satisfied. Relaxing the fuzziness constraint in this way allows the domain experts to focus more clearly on accurate expressions of their agreement and disagreement as independent variables.

(iv) The use of last aggregation renders the model more transparent.

Aggregation is an essential step in any multi-criteria decision-making process. It provides a standard means to consolidate a range of expert opinions into a single decision outcome. For many approaches the aggregation is applied first, as otherwise the weighting and calculation overhead can be prohibitive. The PFS approach presented in this study has no such computational overhead and accordingly the aggregation is applied as a last step. Leaving the aggregation until last retains as much information as possible for as long as possible. Having the individual opinions and weightings explicit means sensitivity and assumption testing is far better informed. Last aggregation means that the significance of individual expert opinions and the sensitivity of changed assumptions on decision outcomes can be identified, tested and adjusted directly and as required by the project manager.

(v) The approach is generalizable and scalable to larger groups of domain experts and extendable to a broader range of evaluation criteria.

The PFS approach presented in this study can be scaled to deal with any number of criteria and any number of expert opinions with minimal impact on the complexity of the computational resources required. This is an especially important feature for applications in practice, where the number of domain experts included is typically large. Large-scale construction projects in particular have a substantial number of disparate stakeholders and professional consultants involved. This broader representation is critical for statistically significant and robust decision outcomes. The scalability of the PFS approach presented also supports situations where the project manager might seek to extend the decision matrix and include additional or replacement evaluation criteria beyond the five criteria used in this demonstration. Whilst the case study presented in this study is specific to large-scale construction projects, the characteristics of large-scale projects in any domain are fairly consistent, meaning the same PFS approach can be generalized across multiple project management contexts.

(vi) The final ranking is clear cut and can be tested using standard sensitivity analysis techniques.

The final decision output records both an actual aggregated ranking score as well as the crisper, discrete ranking of competing projects. The PFS approach presented in this study also lends itself to rapid sensitivity analysis. Once the fuzzy sets have been determined, the calculation overheads of changing the evaluation criteria values and/or the weightings of the domain expert opinions are computationally trivial. This creates outstanding clarity in the comparison of competing projects and significant flexibility in the analysis and interrogation process.

6. Conclusions

A novel approach to the evaluation of large-scale construction projects is presented, taking project resilience as the key objective focus. Project resilience is of increasing interest in project evaluation, most particularly in the risk management associated with such decisions. Adopting resilience as the key objective criteria then invites further consideration of how uncertainty can best be dealt with in broad multi-criteria decision-making processes. In response, the study develops and demonstrates a novel Pythagorean fuzzy sets approach in the form of a multi-criteria evaluation case study and incorporates the differing opinions of multiple domain experts. Pythagorean fuzzy sets are shown to offer particular improvement over both classic fuzzy set theory and more recent developments using intuitionistic fuzzy sets. As demonstrated in this study, a Pythagorean fuzzy set allows the domain experts to focus more clearly on accurate expressions of their agreement and disagreement as independent variables. Pythagorean fuzzy sets are highlighted as an important new direction for multi-criteria decision-making methods under uncertain conditions. The novel Pythagorean fuzzy sets approach presented in this study is scalable, generalizable, and practical.

This study applied the novel Pythagorean fuzzy sets approach to a specific case study requiring selection of the most resilient candidate from a list of large-scale project opportunities. The study demonstrated how construction resilience can usefully be addressed within a multi-criteria assessment framework. The case study demonstrated the capacity of construction project experts to express judgements in agreement, disagreement and hesitancy terms to produce meaningful fuzzy numbers. Moreover, using Pythagorean fuzzy sets proved that this can be done with a high degree of flexibility. Applied to the case of a large-scale construction project selection problem, Pythagorean fuzzy sets provide a transparent decision-making method for the project practitioners. The clear-cut outcome is to select project P_01 over the other candidates available. The transparency and efficiency of the Pythagorean fuzzy sets process developed in this study enabled a robust sensitivity analysis of the outcomes and highlighted the benefits of last aggregation and last defuzzification approaches. Given the transparency and flexibility of the approach, the choice of project P_01 as preferred project is rendered incontrovertible in the circumstances.

Acknowledgments

The authors are thankful to the editor and anonymous reviewers for valuable comments that lead to improving this paper.

References

Adalı, E. A., & Işık, A. T. (2017). The multi-objective decision making methods based on MULTIMOORA and MOOSRA for the laptop selection problem. Journal of Industrial Engineering International, 13(2), 229-237.

Akkaya, G., Turanoğlu, B., & Öztaş, S. (2015). An integrated fuzzy AHP and fuzzy MOORA approach to the problem of industrial engineering sector choosing. Expert Systems with Applications, 42(24), 9565-9573.

Al-Refaie, A., Bani Domi, G., & Abdullah, R. (2019). A fuzzy goal programming-regression approach to optimize process performance of multiple responses under uncertainty. International Journal of Management Science and Engineering Management, 14(1), 20-32.

Arabsheybani, A., Paydar, M. M., & Safaei, A. S. (2018). An integrated fuzzy MOORA method and FMEA technique for sustainable supplier selection considering quantity discounts and supplier's risk. Journal of Cleaner Production, 190, 577-591.

Atanassov, K. T. (1983). Intuitionistic fuzzy sets. Central Tech Library, Bulgarian Academy Science, Sofia, Bulgaria,.

Badalpur, M., & Nurbakhsh, E. (2019). An application of WASPAS method in risk qualitative analysis: a case study of a road construction project in Iran. International Journal of Construction Management, 1-9. Article in press. DOI: https://doi.org/10.1080/15623599.2019.1595354

Batabyal, A. A. (2016). Accessibility, vulnerability, and resilience in a stochastic model of sustainable ecotourism. Transportation Research Part D: Transport and Environment, 43, 71-81.

Baušys, R., & Juodagalvienė, B. (2017). Garage location selection for residential house by WASPAS-SVNS method. Journal of Civil Engineering and Management, 23(3), 421-429.

Birgani, Y. T., & Yazdandoost, F. (2018). An integrated framework to evaluate resilient-sustainable urban drainage management plans using a combined-adaptive MCDM technique. Water resources management, 32(8), 2817-2835.

Bordoli, D. W., & Baldwin, A. N. (1998). A methodology for assessing construction project delays. Construction Management & Economics, 16(3), 327-337.

Brandon-Jones, E., Squire, B., Autry, C. W., & Petersen, K. J. (2014). A contingent resource-based perspective of supply chain resilience and robustness. Journal of Supply Chain Management, 50(3), 55-73.

Chakraborty, S., Zavadskas, E. K., & Antucheviciene, J. (2015). Applications of Waspas Method As A Multi-Criteria Decision-Making Tool. Economic Computation & Economic Cybernetics Studies & Research, 49(1), 1-20.

Chapman, C. (2006). Key points of contention in framing assumptions for risk and uncertainty management. International Journal of Project Management, 24(4), 303-313.

Davoudabadi, R., Mousavi, S.M., Šaparauskas, J., & Gitinavard, H., (2019). Solving construction project selection problem by a new uncertain weighting and ranking based on compromise solution with linear assignment approach, Journal of Civil Engineering and Management, 25(3), 241–251.

Dehlin, E. (2008). The flesh and blood of improvisation. Trondheim: Norwegian University of Science and Technology.

Deveci, M., Canıtez, F., & Gökaşar, I. (2018). WASPAS and TOPSIS based interval type-2 fuzzy MCDM method for a selection of a car sharing station. Sustainable Cities and Society, 41, 777-791.

Dinçer, H., Yüksel, S., & Martínez, L. (2019). Interval type 2-based hybrid fuzzy evaluation of financial services in E7 economies with DEMATEL-ANP and MOORA methods. Applied Soft Computing, 79, 186-202.

Dorfeshan, Y., Mousavi, S. M., Mohagheghi, V., & Vahdani, B. (2018). Selecting project-critical path by a new interval type-2 fuzzy decision methodology based on MULTIMOORA, MOOSRA and TPOP methods. Computers & Industrial Engineering, 120, 160-178.

Ebrahimnejad, S., Mousavi, S. M., Tavakkoli-Moghaddam, R., Hashemi, H., & Vahdani, B. (2012). A novel two-phase group decision making approach for construction project selection in a fuzzy environment. Applied Mathematical Modelling, 36(9), 4197-4217.

Eden, C., Williams, T., Ackermann, F., & Howick, S. (2000). The role of feedback dynamics in disruption and delay on the nature of disruption and delay (D&D) in major projects. Journal of the Operational Research Society, 51(3), 291-300.

Eikeland, P. T. (1998). Teoretisk analyse av byggeprosesser. Samspill i byggeprosessen, prosjektnr, 10602.

Goldratt, E. (1997). Critical chain: A business novel.[sl] North River Press Great Barrington.

Gunasekaran, A., Subramanian, N., & Rahman, S. (2015). Supply chain resilience: role of complexities and strategies, International Journal of Production Research, 53:22, 6809-6819, DOI: 10.1080/00207543.2015.1093667

Haldar, A., Ray, A., Banerjee, D., & Ghosh, S. (2012). A hybrid MCDM model for resilient supplier selection. International Journal of Management Science and Engineering Management, 7(4), 284-292.

Hamel, G., & Valikangas, L. (2004). The quest for resilience. Revista Icade. Revista de las Facultades de Derecho y Ciencias Económicas y Empresariales, (62), 355-358.

Harvett, C. M. (2013). A study of uncertainty and risk management practice related to perceived project complexity.

Hatefi, S. M., & Tamošaitienė, J. (2018). Construction projects assessment based on the sustainable development criteria by an integrated fuzzy AHP and improved GRA model. Sustainability, 10(4), 991.

Heydari Dehooei, J., & Hosseini Dehshiri, S. J. (2019). Selecting project manager based on competency model using SWARA and WASPAS combined methods: Case of Pishgaman Kavir Yazd Cycas Park Project. Management Research in Iran, 22(4), 47-72.

Hollnagel, E., Woods, D. D., & Leveson, N. (2007). Resilience engineering: Concepts and precepts. Ashgate Publishing, Ltd..

Hosseini, S., Ivanov, D., & Dolgui, A. (2019). Review of quantitative methods for supply chain resilience analysis. Transportation Research Part E: Logistics and Transportation Review, 125, 285-307.

Hsu, L. C. (2014). A hybrid multiple criteria decision-making model for investment decision making. Journal of Business Economics and Management, 15(3), 509-529.

Hwang, C. L., Lai, Y. J., & Liu, T. Y. (1993). A new approach for multiple objective decision making. Computers & operations research, 20(8), 889-899.

Karakhan, A. A., Rajendran, S., Gambatese, J., & Nnaji, C. (2018). Measuring and evaluating safety maturity of construction contractors: multicriteria decision-making approach. Journal of Construction Engineering and Management, 144(7), 04018054.

Keshavarz Ghorabaee, M., Amiri, M., Kazimieras Zavadskas, E., & Antuchevičienė, J. (2017). Assessment of third-party logistics providers using a CRITIC–WASPAS approach with interval type-2 fuzzy sets. Transport, 32(1), 66-78.

Kochan, C. G., & Nowicki, D. R. (2018). Supply chain resilience: a systematic literature review and typological framework. International Journal of Physical Distribution & Logistics Management, 48(8), 842-865.

Kuo, Y. C., & Lu, S. T. (2013). Using fuzzy multiple criteria decision making approach to enhance risk assessment for metropolitan construction projects. International Journal of Project Management, 31(4), 602-614.

Mandelbaum, M., & Buzacott, J. (1990). Flexibility and decision making. European Journal of Operational Research, 44(1), 17-27.

Maravas, A., & Pantouvakis, J. P. (2012). Project cash flow analysis in the presence of uncertainty in activity duration and cost. International Journal of Project Management, 30(3), 374-384.

Marzoughi, F., Arthanari, T., & Askarany, D. (2018). A decision support framework for estimating project duration under the impact of weather. Automation in Construction, 87, 287-296.

Mavrotas, G., & Pechak, O. (2013). Combining mathematical programming and Monte Carlo simulation to deal with uncertainty in energy project portfolio selection. In Assessment and simulation tools for sustainable energy systems (pp. 333-356). Springer London.

Medineckiene, M., Zavadskas, E. K., Björk, F., & Turskis, Z. (2015). Multi-criteria decision-making system for sustainable building assessment/certification. Archives of Civil and Mechanical Engineering, 15(1), 11-18.

Ministry of Road and Urban Development, investment opportunities in railway and freeway projects, 2015, http://investment.mrud.ir/.

Mohagheghi, V., & Mousavi, S.M. (2019). A new framework for high-technology project evaluation and project portfolio selection based on Pythagorean fuzzy WASPAS, MOORA and mathematical modeling. Iranian Journal of Fuzzy Systems, 16, 6, 89-106.

Mohagheghi, V., Mousavi, S.M., & Siadat, A. (2015a). A new approach in considering vagueness and lack of knowledge for selecting sustainable portfolio of production projects. In 2015 IEEE International Conference on Industrial Engineering and Engineering Management (IEEM), (pp. 1732-1736).

Mohagheghi, V., Mousavi, S.M., & Siadat, A. (2016). Best product end-of-life scenario selection by a new decision-making process under Atanassov fuzzy uncertainty. In 2016 IEEE International Conference on Management of Innovation and Technology (ICMIT), (pp. 313-317).

Mohagheghi, V., Mousavi, S.M., & Vahdani, B. (2015b). A new uncertain modeling of production project time and cost based on Atanassov fuzzy sets. Journal of Quality Engineering and Production Optimization, 1(2), 57-70.

Mohagheghi, V., Mousavi, S.M., & Vahdani, B. (2016). A new multi-objective optimization approach for sustainable project portfolio selection: a real world application under interval-valued fuzzy environment. Iranian Journal of Fuzzy Systems, 13(6), 41-68.

Mohagheghi, V., Mousavi, S.M., & Vahdani, B. (2017a). Enhancing decision-making flexibility by introducing a new last aggregation evaluating approach based on multi-criteria group decision making and Pythagorean fuzzy sets. Applied Soft Computing. 61, 527-535.

Mohagheghi, V., Mousavi, S.M., Vahdani, B., & Siadat, A. (2017b). A mathematical modeling approach for high and new technology-project portfolio selection under uncertain environments, Journal of Intelligent and Fuzzy Systems, 32, 4069–4079.

Mojtahedi, M., Newton, S., & Von Meding, J. (2017). Predicting the resilience of transport infrastructure to a natural disaster using Cox's proportional hazards regression model. Natural Hazards, 85(2), 1119-1133.

Mok, K. Y., Shen, G. Q., & Yang, J. (2015). Stakeholder management studies in mega construction projects: A review and future directions. International Journal of Project Management, 33(2), 446-457.

Morris, J. M., Dumble, P. L., & Wigan, M. R. (1979). Accessibility indicators for transport planning. Transportation Research Part A: General, 13(2), 91-109.

Mousavi, S.M., Gitinavard H., & Vahdani, B., (2015). Evaluating construction projects by a new group decision-making model based on intuitionistic fuzzy logic concepts, International Journal of Engineering, Transactions C: Aspects, 28(9), 1312-1319.

Naeni, L. M., Shadrokh, S., & Salehipour, A. (2014). A fuzzy approach for the earned value management. International Journal of Project Management, 32(4), 709-716.

Nguyen, A. T., Nguyen, L. D., Le-Hoai, L., & Dang, C. N. (2015). Quantifying the complexity of transportation projects using the fuzzy analytic hierarchy process. International Journal of Project Management, 33(6), 1364-1376.

Omidvar, M., Mazloumi, A., Mohammad Fam, I., & Nirumand, F. (2017). Development of a framework for resilience measurement: Suggestion of fuzzy Resilience Grade (RG) and fuzzy Resilience Early Warning Grade (REWG). Work, 56(3), 463-474.

Parkouhi, S. V., & Ghadikolaei, A. S. (2017). A resilience approach for supplier selection: Using fuzzy analytic network process and grey VIKOR techniques. Journal of cleaner production, 161, 431-451.

Peng, X., & Yang, Y. (2015). Some results for Pythagorean fuzzy sets. International Journal of Intelligent Systems, 30(11), 1133-1160.

Pérez-Domínguez, L., Rodríguez-Picón, L. A., Alvarado-Iniesta, A., Luviano Cruz, D., & Xu, Z. (2018). MOORA under Pythagorean fuzzy set for multiple criteria decision making. Complexity, Vol. 2018. https://doi.org/10.1155/2018/2602376

Pramanik, D., Mondal, S. C., & Haldar, A. (2019). A framework for managing uncertainty in information system project selection: an intelligent fuzzy approach. International Journal of Management Science and Engineering Management, 1-9. Article in press. DOI: https://doi.org/10.1080/17509653.2019.1604191

Rajesh, R. (2016). Forecasting supply chain resilience performance using grey prediction. Electronic Commerce Research and Applications, 20, 42-58.

Ravanshadnia, M., Rajaie, H., & Abbasian, H. R. (2010). Hybrid fuzzy MADM project-selection model for diversified construction companies. Canadian Journal of Civil Engineering, 37(8), 1082-1093.

Rejment, M., & Dziadosz, A. (2015). Selected aspects of construction projects selection including risk estimation. Czasopismo Techniczne.

Scholten, K., Sharkey Scott, P., & Fynes, B. (2014). Mitigation processes–antecedents for building supply chain resilience. Supply Chain Management: An International Journal, 19(2), 211-228.

Seville, E. (2009). Resilience: Great concept...but what does it mean for organisations?, New Zealand Government, Wellington, New Zealand.

Shaaban, M., & Scheffran, J. (2017). Selection of sustainable development indicators for the assessment of electricity production in Egypt. Sustainable Energy Technologies and Assessments, 22, 65-73.

Stanujkic, D., Magdalinovic, N., Stojanovic, S., & Jovanovic, R. (2012). Extension of ratio system part of MOORA method for solving decision-making problems with interval data. Informatica, 23(1), 141-154.

Szmidt, E., & Kacprzyk, J. (2001, October). Intuitionistic fuzzy sets in some medical applications. In International Conference on Computational Intelligence (pp. 148-151). Springer Berlin Heidelberg.

Talet, A. N., Mat-Zin, R., & Houari, M. (2014). Risk Management and Information Technology Projects. International Journal of Digital Information and Wireless Communications (IJDIWC), 4(1), 1-9.

Tan, Y. T., Shen, L. Y., Langston, C., & Liu, Y. (2010). Construction project selection using fuzzy TOPSIS approach. Journal of modelling in management, 5(3), 302-315.

Taylan, O., Bafail, A. O., Abdulaal, R. M., & Kabli, M. R. (2014). Construction projects selection and risk assessment by fuzzy AHP and fuzzy TOPSIS methodologies. Applied Soft Computing, 17, 105-116.

Thomas, R., Marosszeky, M., Karim, K., Davis, S., & McGeorge, D. (2002, August). The importance of project culture in achieving quality outcomes in construction. In Proceedings IGLC (Vol. 10).

Thuong, N. T. H., Zhang, R., Li, Z., & Hong, P. T. D. (2018). Multi-criteria evaluation of financial statement quality based on hesitant fuzzy judgments with assessing attitude. International Journal of Management Science and Engineering Management, 13(4), 254-264.

Trivedi, A., & Singh, A. (2017). A hybrid multi-objective decision model for emergency shelter location-relocation projects using fuzzy analytic hierarchy process and goal programming approach. International Journal of Project Management. 35(5), 827-840.

Ugur, L. O. (2017). Construction project maneger selection with the MOORA optimisation method: A multi-objective optimization application. JOURNAL OF POLYTECHNIC-POLITEKNIK DERGISI, 20(3), 717-723.

Vidal, L. A., Marle, F., & Bocquet, J. C. (2011). Measuring project complexity using the Analytic Hierarchy Process. International Journal of Project Management, 29(6), 718-727.

Wieland, A., & Marcus Wallenburg, C. (2013). The influence of relational competencies on supply chain resilience: a relational view. International Journal of Physical Distribution & Logistics Management, 43(4), 300-320.

Winnard, J. (2016). Sustainable resilient strategic decision support for commercial companies (Doctoral dissertation, University of Surrey).

Winnard, J., Adcroft, A., Lee, J., & Skipp, D. (2014). Surviving or flourishing? Integrating business resilience and sustainability. Journal of Strategy and Management, 7(3), 303-315.

Winnard, J., Lee, J., & Skipp, D. (2018). Putting resilient sustainability into strategy decisions–case studies. Management Decision.

Woods, D. D. (2003). Creating foresight: How resilience engineering can transform NASA's approach to risky decision making. Work, 4(2), 137-144.

Xu, Z., & Liao, H. (2014). Intuitionistic fuzzy analytic hierarchy process. IEEE Transactions on Fuzzy Systems, 22(4), 749-761.

Yager, R.R., Abbasov, A.M. (2013). Pythagorean membership grades, complex numbers, and decision making. International Journal of Intelligent Systems 28, 436–452.

Yager RR. (2014). Pythagorean membership grades in multicriteria decision making. IEEE Transactions on Fuzzy Systems 22, 958–965.

Ye, J. (2010). Two effective measures of intuitionistic fuzzy entropy. Computing, 87(1), 55-62.

Zavadskas, E. K., Antucheviciene, J., Hajiagha, S. H. R., & Hashemi, S. S. (2014). Extension of weighted aggregated sum product assessment with interval-valued intuitionistic fuzzy numbers (WASPAS-IVIF). Applied Soft Computing, 24, 1013-1021.

Zhang XL, Xu ZS. (2014). Extension of TOPSIS to multiple criteria decision making with pythagorean fuzzy sets. International Journal of Intelligent Systems, 29, 1061–1078.

Zhang, J., Song, X., & Díaz, E. (2016). Project buffer sizing of a critical chain based on comprehensive resource tightness. European Journal of Operational Research, 248(1), 174-182.

Zhang, N., Yang, Y., Su, J., & Zheng, Y. (2019). Modelling and analysis of complex products design based on supernetwork. Kybernetes, 48(5), 861-887.

Zhang, X. (2016). A novel approach based on similarity measure for Pythagorean fuzzy multiple criteria group decision making. International Journal of Intelligent Systems, 31(6), 593-611.

Zimmermann, H. J. (2010). Fuzzy set theory. Wiley Interdisciplinary Reviews: Computational Statistics, 2(3), 317-332.

Zolfani, S. H., Pourhossein, M., Yazdani, M., & Zavadskas, E. K. (2018). Evaluating construction projects of hotels based on environmental sustainability with MCDM framework. Alexandria engineering journal, 57(1), 357-365.