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Enhancing Contractor Selection Process by a New Interval-Valued Fuzzy Decision-Making Model Based on SWARA and CoCoSo Methods

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Abstract: Contractor selection is a crucial aspect of construction projects, with a significant impact on project success. However, traditional methods may not effectively handle the complexities and uncertainties involved in decision-making. To address this, advanced techniques like Multi-Criteria Decision-Making (MCDM) have been developed. In this study, we propose a new approach based on two uncertain methods, Interval-Valued Fuzzy Step-Wise Weight Assessment Ratio Analysis (IVF-SWARA) and Interval-Valued Fuzzy Combined Compromise Solution (IVF-CoCoSo), for contractor selection in construction projects. These methods use interval-valued fuzzy numbers (IVFNs) to handle decision-making under uncertainty and imprecision. By leveraging the benefits of IVFNs, the proposed methods enhance accuracy and flexibility, enabling more informed and reliable decisions. An application example illustrates the effectiveness of the methods, and sensitivity analysis examines how varying criteria weights affect contractor rankings. The study concludes that the IVF-SWARA and IVF-CoCoSo methods assist decision-makers in selecting suitable contractors and achieving project success. These methods provide a robust framework to navigate complexities and uncertainties, leading to improved decision-making in contractor selection for construction projects.

Keywords: construction projects; contractor selection problem; MCDM; SWARA; CoCoSo; interval-valued fuzzy sets

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1. Introduction

The construction industry is a critical component of the global economy, with a direct impact on the development and growth of nations. Its scope extends beyond the creation of buildings and infrastructure, encompassing the creation of critical structures necessary for diverse activities, including transportation, commerce, and industry. Millions of jobs are created by this industry every year, including those for unskilled workers and trained professionals such as architects and engineers. Environmental considerations are also paramount, with the construction industry being responsible for adopting sustainable techniques that reduce its ecological impact. A lack of the physical infrastructure that the building sector produces would have a far-reaching impact on societal activities and impede economic development. Thus, the importance of the construction industry cannot be overstated, and it warrants continued attention and investment.

Contractor selection is a fundamental aspect of any construction project, as it can make or break the entire project's success. A well-chosen contractor can deliver the project on time, within budget, and to the required standard. Conversely, selecting the wrong contractor can result in project delays, cost overruns, and even legal disputes. As noted by Hwang and Ng [1], the selection of the right contractor is one of the most critical success factors in construction projects. Therefore, it is essential to implement a rigorous selection process that considers the contractor's qualifications, reputation, experience, and financial stability. Moreover, the contractor's experience and reputation can significantly impact the project's outcome making it crucial for project owners and managers to undertake a thorough contractor selection process. This is particularly important given the complex nature of modern construction projects, which often involve numerous stakeholders, intricate designs, and tight deadlines.

Over the past few years, numerous investigations have been undertaken within the realm of contractor selection. Cristóbal et al. [2] have introduced a method that merges the cloud and utility theory approach to assess a group of six contractors. Another study, undertaken by Nemati-Lafmejani et al. [3], put forth an integrated bi-objective optimization model to address both the Multi-Mode Resource Constrained Project Scheduling Problem (MRCPSP) and the contractor selection problem simultaneously. Ultimately, it is crucial for project owners and managers to devote sufficient time and effort to selecting the most qualified contractor for their specific project.

Contractor selection represents a tremendously sophisticated Multi-Criteria Decision-Making (MCDM) problem that involves choosing the most appropriate contractor for a project while considering its objectives, scope, and constraints. The utilization of MCDM methods provides a systematic approach to decision-making, allowing decision-makers to prioritize and evaluate the criteria for contractor selection. Akintoye et al. [4] have highlighted that MCDM methodologies equip decision-makers with the necessary tools to manage complexity and ambiguity in the contractor selection process. By utilizing these methods, decision-makers can effectively evaluate and prioritize the criteria involved in contractor selection.

The effectiveness of MCDM methods in contractor evaluation and selection for various projects has been demonstrated through empirical research conducted by El-Sawalhi et al. and El-Sayegh [5,6]. The use of MCDM methods has now become widely accepted as a means of solving real-life problems, as noted by Vasiljevic et al. [7]. Decision-makers can determine a compromise solution that takes into account different criteria and decision-maker preferences by employing MCDM methods, as highlighted by Madic and Petrovic [8].

This study aims to tackle the challenge of selecting the most suitable contractor for construction projects, a critical task that involves considering several criteria. In order to accomplish the stated objective, novel adaptations of the fuzzy SWARA and fuzzy CoCoSo techniques have been proposed. These modifications are intended to augment their capacity to handle uncertainties and vagueness in the decision-making process. Fuzzy logic has been employed to model the imprecision and uncertainty in the criteria and weights. The utilization of these suggested methods is expected to enhance the accuracy and transparency of the contractor selection procedure.

The remainder of this paper is organized as follows: Firstly, a literature review is presented in the next section. Then, a brief introduction to IVFNs and their operators is provided in Section 3. Subsequently, the IVF-SWARA and IVF-CoCoSo methods are introduced in Section 4. A numerical example involving the ranking of contractors is presented in Section 5. The results are evaluated, and a sensitivity analysis is conducted in Section 6. Lastly, the paper concludes in Section 7.

2. Literature Review

Several MCDM methods have been utilized for contractor selection, with AHP being widely employed due to its simplicity and effectiveness in managing complex decision-making problems [9]. Furthermore, according to Saaty and Vargas [10], AHP breaks down the decision problem into a hierarchical structure and evaluates the criteria and alternatives based on pairwise comparisons. This approach has been employed in numerous research studies, including Oyatoye and Odulana's [11] investigation into contractor selection for Nigeria's construction project and Afolayan et al.'s [12] proposition of a Feedback

Integrated Fuzzy Analytic Hierarchy Process (FAHP) model for ranking decision criteria in the determination of contractual workers. TOPSIS is another popular MCDM method used for contractor selection, which ranks alternatives based on their distance from ideal and anti-ideal solutions [13]. For instance, Wang et al. [14] used the TOPSIS method to evaluate and select contractors for the construction of a green building project in China.

ELECTRE and PROMETHEE are outranking methods used for contractor selection to handle multiple conflicting criteria. These methods assign weights to the criteria and alternatives, and then rank the alternatives based on their outranking relationships [15]. The ELECTRE method was used in Wu and Chen [16] research to evaluate and select contractors, whereas Morkunaite et al. [17] applied the PROMETHEE method to select the most efficient alternative among cultural heritage contractors. In a similar vein, Gul et al. [18] used a fuzzy logic-based PROMETHEE method to address material selection problems.

Moreover, the VIKOR method is another MCDM technique applied for contractor selection, which is a compromise ranking method that considers both the best and worst performance of the alternatives and selects the best overall compromise solution [19]. For instance, Hashemi et al. [20] employed the fuzzy VIKOR method for contractor assessment. Furthermore, Naghizadeh Vardin et al. [21] proposed an integrated decision support model based on the Fuzzy-VIKOR technique to facilitate contractor selection for a water channel construction project, whereas Geetha et al. [22] utilized the VIKOR method to rank the available alternatives and determine the most suitable option while considering the conflicting criteria. The results of these studies highlight the practical benefits of VIKOR method in the selection of contractors or alternatives for construction projects.

Grey Relational Analysis (GRA) is a data analysis method that compares the degree of similarity between multiple sets of data based on the Grey System Theory [23]. Sun et al. [24] applied the GRA method to evaluate and rank the performance of contractors based on various criteria such as technical ability, financial status, and experience. Additionally, Gholipour et al. [25] utilized a fuzzy MCDM method based on the AHP to select the best contractor for a construction project.

The SWARA method is a type of MCDM method used to determine the weight of each criterion. This method offers several advantages in the context of weighting criteria. This method offers significant advantages as a method for weighting criteria in MCDM. When compared to other MCDM weighting methods, SWARA stands out in several aspects. Firstly, SWARA provides a user-friendly approach that is easy to understand and implement, making it accessible to decision-makers with varying levels of expertise. Its step-wise process allows for a transparent evaluation and weighting of criteria, promoting clarity and understanding throughout the decision-making process. Secondly, SWARA exhibits high flexibility in handling diverse criteria types, including quantitative and qualitative factors. This flexibility enables decision-makers to incorporate a wide range of considerations into the decision-making process, capturing the multi-dimensional nature of real-world decision problems. Additionally, SWARA's consideration of interdependencies between criteria sets it apart from other weighting methods. SWARA ensures a more comprehensive and realistic assessment by evaluating the relationships and interrelationships among criteria. This consideration enables decision-makers to capture the complex dependencies that exist in decision-making scenarios, resulting in more accurate and informed weighting decisions. Furthermore, SWARA's step-wise approach allows decision-makers to evaluate and prioritize criteria based on their relative importance within the decision context. This capability facilitates a systematic and structured decision-making process, leading to more efficient and effective outcomes. In summary, SWARA's advantages of user-friendliness, flexibility in handling diverse criteria, consideration of interdependencies, and a structured approach distinguish it from other MCDM weighting methods. These characteristics make SWARA a valuable tool for decision-makers seeking a transparent, adaptable, and comprehensive approach to weighting criteria in multi-criteria decision-making contexts. In a recent study conducted by Cao et al. [26], a Grey SWARA-FUCOM weighting method was applied to select the best contractor for a construction project.

The CoCoSo method, which was introduced by Yazdani et al. [27], is another MCDM technique that has been utilized in contractor selection. The CoCoSo method offers several advantages in MCDM. It enables a comprehensive evaluation of alternatives by considering multiple criteria simultaneously, leading to a holistic assessment. The method is flexible, allowing decision-makers to customize criteria weights and preferences, enhancing adaptability. It seeks a compromise solution that balances conflicting objectives, striving for optimal performance across criteria. With a clear and structured approach, it promotes transparency in decision-making, particularly beneficial when stakeholders are involved. The CoCoSo method has been successfully applied in various fields, demonstrating its practical utility in supplier selection, project management, and contractor selection. As a decision support tool, it provides a systematic framework for analyzing complex decisions, aiding in the identification of suitable contractors based on defined criteria and preferences. It is worth noting that the specific advantages may vary depending on the application and context of the CoCoSo method. In summary, the CoCoSo method stands out among other MCDM ranking methods due to its comprehensive evaluation, flexibility, compromise solution approach, transparency, and demonstrated applicability. These features make it a valuable decision-support tool for addressing complex decision-making problems with multiple criteria. Yazdani et al. [28] used CoCoSo-G method for supplier selection in construction management. Also, a SWARA-CoCoSo-Based approach has been proposed by Kumar et al. [29] for spray painting robot selection.

Fuzzy sets have gained significant attention and popularity in recent years in the field of MCDM due to their remarkable ability to handle uncertain and imprecise data. This has led to their widespread use in various industries and applications. One of the main advantages of fuzzy sets is their flexibility in representing complex and subjective relationships between variables. Unlike traditional binary logic, which assumes that variables are either true or false, fuzzy sets allow for the representation of degrees of truth, where a variable can be partially true and partially false. This will enable decision-makers to capture the nuances of a decision problem and make more informed choices.

Furthermore, fuzzy sets can be used to handle imprecise and uncertain data, a common occurrence in decision-making scenarios. In these cases, data may be incomplete, inconsistent, or subjective, making it difficult to make a reliable decision. IVFNs offer significant advantages in decision-making scenarios compared to standard fuzzy sets. IVFNs provide an enhanced representation of uncertainty by capturing the range of possible values rather than relying on a single-point value. This allows decision-makers to better understand and manage uncertainty in complex decision problems. By considering a range of values, IVFNs offer flexibility in modeling uncertainty, making them particularly useful when dealing with imprecise or incomplete information. They enable decision-makers to make more accurate and robust decisions by taking into account potential variations and fluctuations in the data. IVFNs facilitate trade-off analysis by providing a comprehensive range of possible outcomes, allowing decision-makers to assess the consequences of different alternatives and select the most appropriate option. They are especially effective in handling limited data and enable decision sensitivity analysis to identify critical factors influencing the results. Widely applicable across industries, IVFNs empower decision-makers to address complex decision problems comprehensively, considering uncertainties and making informed choices.

As previously mentioned, selecting a contractor for construction projects is an MCDM problem that involves evaluating various attributes and identifying the most suitable alternative based on several criteria. In this paper, we propose a new method that integrates Interval-Valued Fuzzy SWARA (IVF-SWARA) and Interval-Valued Fuzzy (IVF-CoCoSo) approaches to solve MCDM problems. The proposed method considers performance ratings and criteria weights expressed as linguistic terms, represented by IVFN. By utilizing this innovative method, our goal is to offer a practical and effective solution for selecting contractors in construction projects. The IVF-SWARA and IVF-CoCoSo approaches are suitable for solving MCDM problems as they can handle the uncertainty and vagueness often encountered in real-world decision-making scenarios. These approaches provide a flexible framework for decision-makers to express their preferences more precisely by using linguistic terms, which enables a more comprehensive and accurate decision-making process.

3. Interval-Valued Fuzzy Numbers

Linguistic values offer a unique advantage in handling complex and ambiguous scenarios that cannot be easily quantified or measured. This is because linguistic terms are intuitively easy to use in expressing the subjectivity and qualitative imprecision inherent in decision-making processes. As noted by Zadeh and Zimmermann [30,31], a linguistic variable is a variable whose values are represented by linguistic terms, which can provide a more nuanced understanding of the situation being evaluated.

However, some scholars argue that the presentation of a linguistic expression in the form of ordinary fuzzy sets may not be enough. Grattan in the mid-70s and Karnik and Mendel in 2001 [32,33] have suggested that interval-valued fuzzy sets can provide greater flexibility in representing imprecise or vague information. This approach allows for a wider range of possible values, giving decision-makers more room to express their opinions and assessments.

Furthermore, researchers have found that interval-valued fuzzy sets are better able to ensure the clarity of a linguistic expression, as they provide decision-makers with a more accurate representation of imprecise or vague information. As noted by Ashtiani et al. and Vahdani et al. [34,35], interval-valued fuzzy sets are a valuable tool for decision-makers seeking to make informed and effective decisions in complex and ambiguous situations.

The present research investigates the concept of fuzzy demand using interval-valued fuzzy sets. The study draws upon Gorzalczany's [36] definition of $\widetilde{A}$, an interval-valued fuzzy set that is defined over the entire range $(-\infty, \infty)$ as $\widetilde{A} = \left\{x, \left[\mu_{\widetilde{A}^l}(x), \mu_{\widetilde{A}^u}(x)\right]\right\}$, $x \in (-\infty, \infty), \mu_{\widetilde{A}^l}, \mu_{\widetilde{A}^u} : (-\infty, \infty) \to [0, 1]$; $\mu_{\widetilde{A}}(x) = \left[\mu_{\widetilde{A}^l}(x), \mu_{\widetilde{A}^u}(x)\right]$, $\mu_{\widetilde{A}^l}(x) \le \mu_{\widetilde{A}^u}(x)$, $\forall x \in (-\infty, \infty)$, where $\mu_{\widetilde{A}^l}(x)$ and $\mu_{\widetilde{A}^u}(x)$ denote the lower and upper bounds of the membership degree.

Furthermore, Yao and Lin's definition of triangular IVFNs [37] (as illustrated in Figure 1) states that triangular IVFN can be depicted as $\widetilde{A} = \left[\widetilde{A}^l_x, \widetilde{A}^u_x\right] = \left[\left(a'^l, a^l, a''^l; \hat{y}^l_{\widetilde{A}}\right), \left(a'^u, a^u, a''^u; \hat{y}^u_{\widetilde{A}}\right)\right]$. Where $\widetilde{A}^l$ and $\widetilde{A}^u$ are the lower and upper triangular IVFNs, $\widetilde{A}^l \subset \widetilde{A}^l$; $\mu_{\widetilde{A}}(x)$ is the membership function, when it denotes the degree in which an event x may be a member of $\widetilde{A}; \mu_{\widetilde{A}^l}(x) = \hat{y}^l_{\widetilde{A}}$ and $\widetilde{A}; \mu_{\widetilde{A}^u}(x) = \hat{y}^u_{\widetilde{A}}$ are the lower and upper membership functions, respectively. According to Figure 1, the relations can be obtained as follows:

- i If $\widetilde{A}^l = \widetilde{A}^u$, then the triangular IVFN $\widetilde{A}$ can be considered as a generalized triangular fuzzy number.
- ii If $a'^l = a'^u$, $a^l = a^u$, $a''^l = a''^u$ and $\hat{y}^l_{\widetilde{A}} = \hat{y}^u_{\widetilde{A}}$, then the triangular IVFN $\widetilde{A}$ is a crisp value.
- iii If $\hat{y}^l_{\widetilde{A}} = \hat{y}^u_{\widetilde{A}} = 1$ and $a^l = a^u$, then the triangular IVFN $\widetilde{A}$ can be represented as $\widetilde{A} = \left[\widetilde{A}^l_x, \widetilde{A}^u_x\right] = \left[\left(a'^u, a'^l\right), \left(a^l = a^u\right), \left(a''^l, a''^u\right)\right]$.

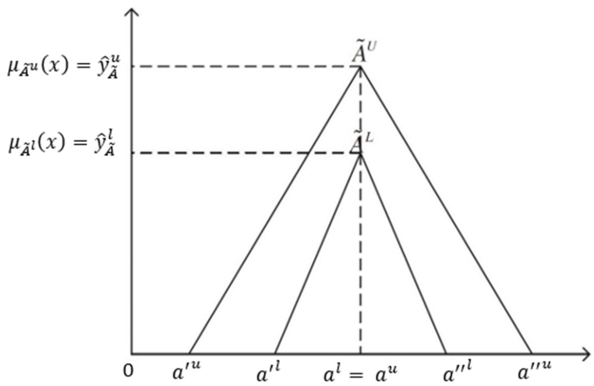

Figure 1. An interval-valued triangular fuzzy number.

Based on the third relation described above (iii), two triangular IVFNs can be represented as $\widetilde{A} = \left[\left(a'^{u}, a'^{l}\right), a, \left(a''^{l},\ a''^{u}\right)\right]$ and $\widetilde{B} = \left[\left(b'^{u}, b'^{l}\right), b, \left(b''^{l},\ b''^{u}\right)\right]$. Subsequently, the Chen, Hong and Lee, Chen and Chen, and Vahdani et al. studies [35,38–40] proposed addition, subtraction, multiplication, and generalized division operations between $\widetilde{A}$ and $\widetilde{B}$, which are presented below:

a. Addition of IVFNs $\oplus$:

$$\begin{aligned} \widetilde{A} \oplus \widetilde{B} &= \left[\left(a'^{u}, a'^{l}\right), a, \left(a''^{l},\ a''^{u}\right)\right] \oplus \left[\left(b'^{u}, b'^{l}\right), b, \left(b''^{l},\ b''^{u}\right)\right] \\ &= \left[\left(a'^{u} + b'^{u}, a'^{l} + b'^{l}\right), a + b, \left(a''^{l} + b''^{l},\ a''^{u} + b''^{u}\right)\right] \end{aligned} \tag{1}$$

b. Subtraction of IVFNs $\ominus$:

$$\begin{aligned} \widetilde{A} \ominus \widetilde{B} &= \left[\left(a'^{u}, a'^{l}\right), a, \left(a''^{l},\ a''^{u}\right)\right] \ominus \left[\left(b'^{u}, b'^{l}\right), b, \left(b''^{l},\ b''^{u}\right)\right] \\ &= \left[\left(a'^{u} - b'^{u}, a'^{l} - b'^{l}\right), a - b, \left(a''^{l} - b''^{l},\ a''^{u} - b''^{u}\right)\right] \end{aligned} \tag{2}$$

c. Multiplication of IVFNs $\otimes$:

$$\begin{aligned} \widetilde{A} \otimes \widetilde{B} &= \left[\left(a'^{u}, a'^{l}\right), a, \left(a''^{l},\ a''^{u}\right)\right] \otimes \left[\left(b'^{u}, b'^{l}\right), b, \left(b''^{l},\ b''^{u}\right)\right] \\ &= \left[\left(a'^{u} \times b'^{u}, a'^{l} \times b'^{l}\right), a \times b, \left(a''^{l} \times b''^{l},\ a''^{u} \times b''^{u}\right)\right] \end{aligned} \tag{3}$$

d. Generalized division of IVFNs $\oslash$:

$$\begin{aligned} \widetilde{A} \oslash \widetilde{B} &= \left[\left(a'^{u}, a'^{l}\right), a, \left(a''^{l},\ a''^{u}\right)\right] \oslash \left[\left(b'^{u}, b'^{l}\right), b, \left(b''^{l},\ b''^{u}\right)\right] \\ &= \left[\left(a'^{u} \div b''^{u}, a'^{l} \div b''^{l}\right), a \div b, \left(a''^{l} \div b'^{l},\ a''^{u} \div b'^{u}\right)\right] \end{aligned} \tag{4}$$

4. Proposed Methodology

This paper presents a novel approach that combines two innovative methodologies, the IVF-SWARA and the IVF-CoCoSo, to address the challenges associated with MCDM problems. The proposed model comprises two distinct phases. The initial phase involves the weighting of the criteria through the implementation of the IVF-SWARA method. Subsequently, in the second phase, the alternatives undergo evaluation and subsequent ranking utilizing the IVF-CoCoSo method. To facilitate a more precise and comprehensive expression of preferences by decision-makers, the proposed methods utilize IVFNs to represent performance ratings and criteria weights as linguistic variables. The linguistic variables can be transformed into IVFNs by utilizing the representations presented in Table 1. Table 1 specifically pertains to IVFNs associated with the relative importance of each criterion. Similarly, Table 2 comprises IVFNs relevant to both the performance of each alternative and the importance of each criterion.

Table 1. IVFNs corresponding to linguistic variables for relative importance of each criterion.

Linguistic Variable	Abbreviation	IVFN
Absolutely Low	AL	[(0, 0.025), 0.075, (0.15, 0.2)]
Very Low	VL	[(0.1, 0.125), 0.175, (0.25, 0.3)]
Low	L	[(0.2, 0.225), 0.275, (0.35, 0.4)]
Medium Low	ML	[(0.3, 0.325), 0.375, (0.45, 0.5)]
Medium	M	[(0.4, 0.425), 0.475, (0.55, 0.6)]
Medium High	MH	[(0.5, 0.525), 0.575, (0.65, 0.7)]
High	H	[(0.6, 0.625), 0.675, (0.75, 0.8)]
Very High	VH	[(0.7, 0.725), 0.775, (0.85, 0.9)]
Absolutely High	AH	[(0.8, 0.825), 0.875, (0.95, 1)]

Table 2. IVFNs corresponding to linguistic variables for performance of each alternative and importance of each criterion.

Linguistic Variable	Abbreviation	IVFN
Extremely Unimportant/Extremely Bad	EU/EB	[(0, 0.25), 0.75, (1.5, 2)]
Very Unimportant/Very Bad	VU/VB	[(1, 1.25), 1.75, (2.5, 3)]
Unimportant/Bad	U/B	[(2, 2.25), 2.75, (3.5, 4)]
Moderately Unimportant/Moderately Bad	MU/MB	[(3, 3.25), 3.75, (4.5, 5)]
Fair	F	[(4, 4.25), 4.75, (5.5, 6)]
Moderately Important/Moderately Good	MI/MG	[(5, 5.25), 5.75, (6.5, 7)]
Important/Good	I/G	[(6, 6.25), 6.75, (7.5, 8)]
Very Important/Very Good	VI/VG	[(7, 7.25), 7.75, (8.5, 9)]
Extremely Important/Excellent	EI/E	[(8, 8.25), 8.75, (9.5, 10)]

The IVF-SWARA and IVF-CoCoSo approaches are highly suitable for handling the uncertainty and vagueness that are typically encountered in real-world decision-making scenarios. By incorporating linguistic terms into the decision-making process, the proposed method provides a more accurate and comprehensive representation of the decision problem. This can help decision-makers to make more informed and effective decisions that align with their preferences and priorities.

The proposed method has significant practical implications, particularly in the domain of selecting contractors for construction projects. The selection of contractors is a complex decision-making problem that involves multiple criteria and requires the consideration of various factors. The proposed approach can provide an effective solution to this problem by enabling decision-makers to evaluate and compare different contractors based on a comprehensive set of criteria.

4.1. Primitive SWARA and CoCoSo Methods

4.1.1. SWARA Method

In 2010, Kersuliene et al. [41] introduced the SWARA method. This method employs a weighting process to evaluate the relative importance and initial prioritization of alternatives for each attribute based on the decision-maker's perspective. One of the primary characteristics of this method is its ability to incorporate the viewpoints of experts or interest groups regarding the relative importance of attributes when determining their weights. As a result, it is a useful tool for decision-making in situations where multiple perspectives need to be considered.

Once the criteria have been identified and listed, the SWARA method involves a series of steps that include:

Step 1: Ranking the criteria according to their importance.

In this stage, experts are asked to assign a rank to each defined criterion based on its perceived importance. The highest rank is assigned to the most important criterion, while the lowest rank is assigned to the least important one. The remaining criteria are assigned ranks based on their relative importance, with those deemed more important receiving higher ranks and those deemed less important receiving lower ranks.

Step 2: Determining the relative importance of each criterion D_j.

This process begins with the criterion of the second rank, and proceeds by comparing its importance to that of the next criterion in the list. Specifically, the goal is to determine the extent to which the criterion at rank C_j is more important than the criterion at rank C_{j+1}.

Step 3: Calculating the coefficient T_j using the following formula:

$$T_j = \begin{cases} 1 \; j = 1 \\ D_j + 1 \; j > 1 \end{cases} \tag{5}$$

Step 4: Finding the recalculated weight Q_j using the following formula:

$$Q_j = \begin{cases} 1 \; j = 1 \\ \frac{Q_{j-1}}{T_j} \; j > 1 \end{cases} \quad (6)$$

Step 5: Identification of importance weight of each criterion:

$$W_j = \frac{Q_j}{\sum_{j=1}^{n} Q_j} \quad (7)$$

where the variable n represents the number of criteria.

4.1.2. CoCoSo Method

This method employs an integrated model that combines simple additive weighting and exponentially weighted product techniques. It serves as a comprehensive repository of compromise solutions. To tackle a CoCoSo decision problem, the first step involves identifying the alternatives and associated criteria and the following steps.

Step 1: Determining initial decision-making matrix:

$$X = \begin{bmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & & x_{2n} \\ & \vdots & \ddots & \vdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{bmatrix}, \; i = 1,\, 2,\, \ldots,\, m,\; j = 1,\, 2,\, \ldots,\, n. \quad (8)$$

Step 2: Normalizing the decision-making matrix based on compromise normalization equation (see Zeleny, [42]):

$$N = \begin{bmatrix} r_{11} & r_{12} & \cdots & r_{1n} \\ r_{21} & r_{22} & & r_{2n} \\ \vdots & & \ddots & \vdots \\ r_{m1} & r_{m2} & \cdots & r_{mn} \end{bmatrix}, \; r_{ij} = \begin{cases} \frac{x_{ij} - \underset{i}{min} x_{ij}}{\underset{i}{max} x_{ij} - \underset{i}{min} x_{ij}} \; for\ benefit\ criterion \\ \frac{\underset{i}{max} x_{ij} - x_{ij}}{\underset{i}{max} x_{ij} - \underset{i}{min} x_{ij}} \; for\ Cost\ criterion \end{cases} \quad (9)$$

Step 3: Calculating the S_i and P_i using the following formula:

$$S_i = \sum_{j=1}^{n} (w_j r_{ij}) \quad (10)$$

$$P_i = \sum_{j=1}^{n} (r_{ij})^{w_j} \quad (11)$$

Step 4: Computing relative weights of the alternatives:

$$K_{ia} = \frac{S_i + P_i}{\sum_{i=1}^{m} (S_i + P_i)} \quad (12)$$

$$K_{ib} = \frac{S_i}{\underset{i}{min} S_i} + \frac{P_i}{\underset{i}{min} P_i} \quad (13)$$

$$K_{ic} = \frac{\lambda S_i + (1-\lambda) P_i}{\lambda \underset{i}{max} S_i + (1-\lambda) \underset{i}{max} P_i}, \; 0 \le \lambda \le 1 \quad (14)$$

The meaning conveyed is that Equation (12) represents the arithmetic mean of sums of WSM and WPM scores, and Equation (13) represents the sum of relative scores of WSM and WPM compared to the best. Equation (14) provides a balanced compromise between the WSM and WPM model scores, where the decision-makers typically choose λ (usually

$\lambda = 0.5$). Nevertheless, the proposed CoCoSo model's flexibility and stability can depend on other values besides λ.

Step 5: Determining the final rank of alternatives K_i (as more significant as better):

$$K_i = (K_{ia}K_{ib}K_{ic})^{1/3} + 1/3(K_{ia} + K_{ib} + K_{ic}) \tag{15}$$

4.2. Proposed IVF-SWARA and IVF-CoCoSo Methods

4.2.1. Proposed IVF-SWARA Method

As previously mentioned, the proposed method uses IVFN to represent performance ratings and criteria weights in linguistic terms. This approach enables decision-makers to express their preferences more precisely and comprehensively. Thus, the steps of the IVF-SWARA method are as follows:

Step 1: Gathering linguistic variables from each decision maker to rank the criteria in terms of their importance.

This step involves collecting the opinions and perspectives of experts or interest groups involved in the decision-making process, in order to capture a comprehensive range of viewpoints. Subsequently, by assigning an IVFN to each linguistic variable, the criteria are ranked according to their importance. This step lays the foundation for the subsequent stages of the method.

Step 2: Determining the relative importance of each criterion $\widetilde{D}_j$.

In this step, decision-makers express the relative importance of each criterion compared to the previous one using a linguistic variable. Then, by assigning a suitable IVFN to each linguistic variable, the value of $\widetilde{D}_j$ can be obtained. In which, $\widetilde{D}_j$ is IVFN and can be represented as $\widetilde{D} = \left[\left(d'^u, d'^l\right), d, \left(d''^l,\ d''^u\right)\right]$.

Step 3: Calculating the coefficient $\widetilde{T}_j$ using the following formula:

$$\widetilde{T}_j = \begin{cases} \widetilde{1}\ j = 1 \\ \widetilde{D}_j + \widetilde{1}\ j > 1 \end{cases} \tag{16}$$

where $\widetilde{T}_j$ is IVFN and can be represented as $\widetilde{T} = \left[\left(t'^u, t'^l\right), t, \left(t''^l,\ t''^u\right)\right]$.

Step 4: Finding the recalculated weight $\widetilde{Q}_j$ using the following formula:

$$\widetilde{Q}_j = \begin{cases} \widetilde{1}\ j = 1 \\ \frac{\widetilde{Q}_{j-1}}{\widetilde{T}_j}\ j > 1 \end{cases} \tag{17}$$

where $\widetilde{Q}_j$ is IVFN and can be represented as $\widetilde{Q} = \left[\left(q'^u, q'^l\right), q, \left(q'',\ q''^u\right)\right]$.

Step 5: Identification of importance weight of each criterion:

$$\widetilde{W}_j = \frac{\widetilde{Q}_j}{\sum_{j=1}^{n} \widetilde{Q}_j} \tag{18}$$

where $\widetilde{W} = \left[\left(w'^u, w'^l\right), w, \left(w''^l,\ w''^u\right)\right]$ is the relative IVF weights of each criterion and the variable n represents the total number of criteria being considered.

4.2.2. Proposed IVF-CoCoSo Method

As stated earlier, the method being proposed utilizes IVFN to represent performance ratings in linguistic terms. This methodology allows decision-makers to articulate their preferences with greater precision and inclusiveness. Therefore, the IVF-CoCoSo method comprises the following steps:

Step 1: Determining initial decision-making matrix:

$$X = \begin{bmatrix} \widetilde{x}_{11} & \widetilde{x}_{12} & \dots & \widetilde{x}_{1n} \\ \widetilde{x}_{21} & \widetilde{x}_{22} & & \widetilde{x}_{2n} \\ \vdots & & \ddots & \vdots \\ \widetilde{x}_{m1} & \widetilde{x}_{m2} & \dots & \widetilde{x}_{mn} \end{bmatrix},\ i = 1,\ 2,\ \dots,\ m,\ j = 1,\ 2,\ \dots,\ n. \tag{19}$$

where $\widetilde{x}_{ij}$ is IVFN and can be represented as $\widetilde{x}_{ij} = \left[\left(x'^{u}_{ij}, x'^{l}_{ij}\right), x_{ij}, \left(x''^{l}_{ij},\ x''^{u}_{ij}\right)\right]$.

Step 2: Normalizing the decision-making matrix based on compromise normalization equation (see Zeleny [42]):

$$N = \begin{bmatrix} \widetilde{r}_{11} & \widetilde{r}_{12} & \dots & \widetilde{r}_{1n} \\ \widetilde{r}_{21} & \widetilde{r}_{22} & & \widetilde{r}_{2n} \\ \vdots & & \ddots & \vdots \\ \widetilde{r}_{m1} & \widetilde{r}_{m2} & \dots & \widetilde{r}_{mn} \end{bmatrix},\ \widetilde{r}_{ij} = \begin{cases} \dfrac{\widetilde{x}_{ij} - \min\limits_i x'^{u}_{ij}}{\max\limits_i x''^{u}_{ij} - \min\limits_i x'^{u}_{ij}} & for\ benefit\ criterion \\ \dfrac{\max\limits_i x''^{u}_{ij} - \widetilde{x}_{ij}}{\max\limits_i x''^{u}_{ij} - \min\limits_i x'^{u}_{ij}} & for\ Cost\ criterion \end{cases} \tag{20}$$

where $\widetilde{r}_{ij}$ is IVFN and can be represented as $\widetilde{r}_{ij} = \left[\left(r'^{u}_{ij}, r'^{l}_{ij}\right), r_{ij}, \left(r''^{l}_{ij},\ r'^{u}_{ij}\right)\right]$.

Step 3: Calculating the S^l_i, S^u_i, P^l_i and P^u_i using the following formula:

$$S^l_i = 1/3\left(\sum_{j=1}^{n} w'^{l}_{j} r'^{l}_{ij} + \sum_{j=1}^{n} w_j r_{ij} + \sum_{j=1}^{n} w''^{l}_{j} r''^{l}_{ij}\right) \tag{21}$$

$$P^l_i = 1/3\left(\sum_{j=1}^{n} {r'^{l}_{ij}}^{w'^{l}_{j}} + \sum_{j=1}^{n} {r_{ij}}^{w_j} + \sum_{j=1}^{n} {r''^{l}_{ij}}^{w''^{l}_{j}}\right) \tag{22}$$

$$S^u_i = 1/3\left(\sum_{j=1}^{n} w'^{u}_{j} r'^{u}_{ij} + \sum_{j=1}^{n} w_j r_{ij} + \sum_{j=1}^{n} w''^{u}_{j} r''^{u}_{ij}\right) \tag{23}$$

$$P^u_i = 1/3\left(\sum_{j=1}^{n} {r'^{u}_{ij}}^{w'^{u}_{j}} + \sum_{j=1}^{n} {r_{ij}}^{w_j} + \sum_{j=1}^{n} {r''^{u}_{ij}}^{w''^{u}_{j}}\right) \tag{24}$$

Step 4: Computing upper and lower relative weights of the alternatives:

$$K^l_{ia} = \frac{S^l_i + P^l_i}{\sum_{i=1}^{m}\left(S^l_i + P^l_i\right)} \tag{25}$$

$$K^l_{ib} = \frac{S^l_i}{\min\limits_i S^l_i} + \frac{P^l_i}{\min\limits_i P^l_i} \tag{26}$$

$$K^l_{ic} = \frac{\lambda S^l_i + (1-\lambda)P^l_i}{\lambda \max\limits_i S^l_i + (1-\lambda)\max\limits_i P^l_i} \tag{27}$$

$$K^u_{ia} = \frac{S^u_i + P^u_i}{\sum_{i=1}^{m}\left(S^u_i + P^u_i\right)} \tag{28}$$

$$K^u_{ib} = \frac{S^u_i}{\min\limits_i S^u_i} + \frac{P^u_i}{\min\limits_i P^u_i} \tag{29}$$

$$K^u_{ic} = \frac{\lambda S^u_i + (1-\lambda)P^u_i}{\lambda \max\limits_i S^u_i + (1-\lambda)\max\limits_i P^u_i},\ 0 \le \lambda \le 1 \tag{30}$$

Step 5: Determining the final rank of alternatives based on K_i (as more significant or better):

$$K_i^l = \left(K_{ia}^l K_{ib}^l K_{ic}^l\right)^{1/3} + 1/3\left(K_{ia}^l + K_{ib}^l + K_{ic}^l\right) \tag{31}$$

$$K_i^u = (K_{ia}^u K_{ib}^u K_{ic}^u)^{1/3} + 1/3(K_{ia}^u + K_{ib}^u + K_{ic}^u) \tag{32}$$

$$K_i = \frac{K_i^l + K_i^u}{2} \tag{33}$$

Finally, the research flow of this study is shown in Figure 2.

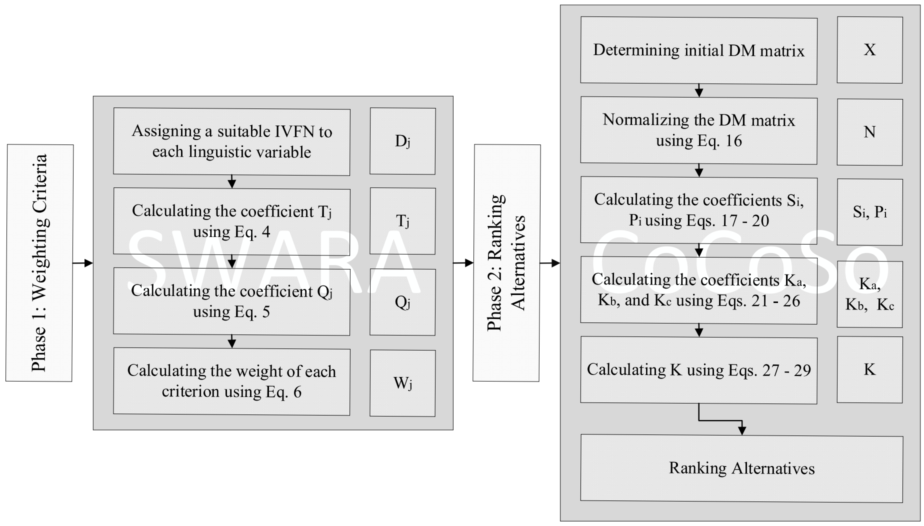

Figure 2. The proposed method based on IVF-SWARA and IVF-CoCoSo.

5. Numerical Example

A construction company is in the process of selecting a contractor to construct a new office building. The company's decision makers, which consist of six experts, have shortlisted six contractors based on their past performance. In the construction industry, the most important criteria for selecting a contractor have been widely studied and discussed. According to a study conducted by Hatush and Skitmore [43], the top five factors considered while choosing a contractor for a construction project are Reputation (R), Financial Soundness (FS), Technical Ability (TA), Health and Safety (HS), and Management Capability (MC). Based on these criteria, the company needs to select the best contractor from the shortlisted candidates.

In the first phase, using the method presented in Section 4.2.1, each decision-maker presented their assessment based on linguistic variables to rate the importance of criteria, as shown in Table 3. The rank for each criterion was determined by assigning an IVFN to each linguistic variable, as shown in Table 4. Subsequently, the criteria were ranked accordingly.

$$MC \succ TA \succ HS \succ R \succ FS$$

Table 3. Linguistic variable of the importance of criterion.

Decision Maker	R	FS	TA	HS	MC
DM1	MU	U	VI	F	EI
DM2	MI	MU	VI	F	I
DM3	MU	VU	I	I	EI
DM4	F	U	VI	MI	EI
DM5	I	MU	I	MI	VI
DM6	MU	F	I	F	EI

Table 4. Assigned IVFN to each linguistic variable of Table 3.

Decision Maker	R	FS	TA	HS	MC
DM1	[(3, 3.25), 3.75, (4.5, 5)]	[(2, 2.25), 2.75, (3.5, 4)]	[(7, 7.25), 7.75, (8.5, 9)]	[(4, 4.25), 4.75, (5.5, 6)]	[(8, 8.25), 8.75, (9.5, 10)]
DM2	[(5, 5.25), 5.75, (6.5, 7)]	[(3, 3.25), 3.75, (4.5, 5)]	[(7, 7.25), 7.75, (8.5, 9)]	[(4, 4.25), 4.75, (5.5, 6)]	[(6, 6.25), 6.75, (7.5, 8)]
DM3	[(3, 3.25), 3.75, (4.5, 5)]	[(1, 1.25), 1.75, (2.5, 3)]	[(6, 6.25), 6.75, (7.5, 8)]	[(6, 6.25), 6.75, (7.5, 8)]	[(8, 8.25), 8.75, (9.5, 10)]
DM4	[(4, 4.25), 4.75, (5.5, 6)]	[(2, 2.25), 2.75, (3.5, 4)]	[(7, 7.25), 7.75, (8.5, 9)]	[(5, 5.25), 5.75, (6.5, 7)]	[(8, 8.25), 8.75, (9.5, 10)]
DM5	[(6, 6.25), 6.75, (7.5, 8)]	[(3, 3.25), 3.75, (4.5, 5)]	[(6, 6.25), 6.75, (7.5, 8)]	[(5, 5.25), 5.75, (6.5, 7)]	[(7, 7.25), 7.75, (8.5, 9)]
DM6	[(3, 3.25), 3.75, (4.5, 5)]	[(4, 4.25), 4.75, (5.5, 6)]	[(6, 6.25), 6.75, (7.5, 8)]	[(4, 4.25), 4.75, (5.5, 6)]	[(8, 8.25), 8.75, (9.5, 10]
Average	[(4, 4.25), 4.75, (5.5, 6)]	[(2.5, 2.75), 3.25, (4, 4.5)]	[(6.5, 6.75), 7.25, (8, 8.5)]	[(4.67, 4.92), 5.42, (6.2, 6.67)]	[(7.5, 7.75), 8.25, (9, 9.5)]

Table 5 displays the linguistic variable indicating the relative importance of each criterion as stated by decision makers, in comparison to the criterion in the higher position. Next, in accordance with Table 1, we have converted the linguistic variables into IVFNs, which can be observed in Table 6.

Table 5. Linguistic variable of the relative importance of criterion.

Criteria	DM1	DM2	DM3	DM4	DM5	DM6
MC	-	-	-	-	-	-
TA	VL	AL	L	VL	VL	L
HS	ML	ML	AL	L	VL	L
R	VL	VL	ML	VL	VL	VL
FS	VL	L	L	L	ML	VL

Table 6. Relative importance of each criterion $\widetilde{D}_j$.

Criteria	DM1	DM2	DM3
MC	[(0, 0), 0, (0, 0)]	[(0, 0), 0, (0, 0)]	[(0, 0), 0, (0, 0)]
TA	[(0.1, 0.125), 0.175, (0.25, 0.3)]	[(0, 0.025), 0.075, (0.15, 0.2)]	[(0.2, 0.225), 0.275, (0.35, 0.4)]
HS	[(0.3, 0.325), 0.375, (0.45, 0.5)]	[(0.3, 0.325), 0.375, (0.45, 0.5)]	[(0, 0.025), 0.075, (0.15, 0.2)]
R	[(0.1, 0.125), 0.175, (0.25, 0.3)]	[(0.1, 0.125), 0.175, (0.25, 0.3)]	[(0.3, 0.325), 0.375, (0.45, 0.5)]
FS	[(0.1, 0.125), 0.175, (0.25, 0.3)]	[(0.2, 0.225), 0.275, (0.35, 0.4)]	[(0.2, 0.225), 0.275, (0.35, 0.4)]
	DM4	**DM5**	**DM6**
MC	[(0, 0), 0, (0, 0)]	[(0, 0), 0, (0, 0)]	[(0, 0), 0, (0, 0)]
TA	[(0.1, 0.125), 0.175, (0.25, 0.3)]	[(0.1, 0.125), 0.175, (0.25, 0.3)]	[(0.2, 0.225), 0.275, (0.35, 0.4)]
HS	[(0.2, 0.225), 0.275, (0.35, 0.4)]	[(0.1, 0.125), 0.175, (0.25, 0.3)]	[(0.2, 0.225), 0.275, (0.35, 0.4)]
R	[(0.1, 0.125), 0.175, (0.25, 0.3)]	[(0.1, 0.125), 0.175, (0.25, 0.3)]	[(0.1, 0.125), 0.175, (0.25, 0.3)]
FS	[(0.2, 0.225), 0.275, (0.35, 0.4)]	[(0.3, 0.325), 0.375, (0.45, 0.5)]	[(0.1, 0.125), 0.175, (0.25, 0.3)]
	Average		
MC	[(0, 0), 0, (0, 0)]		
TA	[(0.117, 0.142), 0.191, (0.267, 0.317)]		
HS	[(0.183, 0.208), 0.258, (0.333, 0.383)]		
R	[(0.133, 0.158), 0.208, (0.283, 0.333)]		
FS	[(0.183, 0.208), 0.258, (0.333, 0.383)]		

The following step involves using Equations (16)–(18) to determine the IVF weight assigned to each criterion, as presented in Table 7.

During the second phase, the contractor's performance is evaluated using the method outlined in Section 4.2.2, and the best contractor is ultimately selected. In the first step of this phase, each decision maker expresses the contractor's performance in each criterion as a linguistic variable, as shown in Table 8.

After the conversion of linguistic variables into IVFNs as per Table 2 and their representation in Table 9, the decision matrix was normalized using Equation (20). The normalized decision matrix is illustrated in Table 10.

Table 7. IVF weight assigned to each criterion.

Criteria	D_j	T_j	Q_j	W_j
MC	[(0, 0), 0, (0, 0)]	[(1, 1), 1, (1, 1)]	[(1, 1), 1, (1, 1)]	[(0.257, 0.267), 0.286, (0.314, 0.331)]
TA	[(0.117, 0.142), 0.192, (0.267, 0.317)]	[(1.117, 1.142), 1.192, (1.267, 1.317)]	[(0.759, 0.789), 0.839, (0.876, 0.896)]	[(0.196, 0.211), 0.240, (0.275, 0.297)]
HS	[(0.183, 0.208), 0.258, (0.333, 0.383)]	[(1.183, 1.208), 1.258, (1.333, 1.383)]	[(0.549, 0.592), 0.667, (0.725, 0.757)]	[(0.141, 0.158), 0.191, (0.227, 0.251)]
R	[(0.133, 0.158), 0.208, (0.283, 0.333)]	[(1.133, 1.158), 1.208, (1.283, 1.333)]	[(0.412, 0.461), 0.552, (0.626, 0.668)]	[(0.106, 0.123), 0.158, (0.196, 0.221)]
FS	[(0.183, 0.208), 0.258, (0.333, 0.383)]	[(1.183, 1.208), 1.258, (1.333, 1.383)]	[(0.298, 0.346), 0.439, (0.518, 0.564)]	[(0.077, 0.092), 0.125, (0.162, 0.187)]

Table 8. Performance of each alternative.

Decision Maker	Reputation					
	Contractor 1	**Contractor 2**	**Contractor 3**	**Contractor 4**	**Contractor 5**	**Contractor 6**
DM1	MG	MB	MG	B	VG	EB
DM2	MG	B	VG	MB	G	VB
DM3	MG	B	VG	MB	VG	EB
DM4	F	MB	G	MB	G	B
DM5	MB	F	G	VB	VG	VB
DM6	MB	F	MG	MB	VG	EB
	Financial soundness					
	Contractor 1	**Contractor 2**	**Contractor 3**	**Contractor 4**	**Contractor 5**	**Contractor 6**
DM1	F	MG	MB	G	MG	MG
DM2	MG	MG	MB	VG	MB	G
DM3	MG	VG	F	MG	MG	VG
DM4	MG	G	MB	VG	B	E
DM5	F	VG	MG	G	F	G
DM6	G	G	F	G	MB	E
	Technical ability					
	Contractor 1	**Contractor 2**	**Contractor 3**	**Contractor 4**	**Contractor 5**	**Contractor 6**
DM1	MG	MG	MB	EB	F	MB
DM2	MG	MG	MB	MB	G	MB
DM3	F	G	MB	EB	F	B
DM4	MG	G	MB	B	MG	F
DM5	G	MG	MB	EB	MG	MB
DM6	G	G	MG	MB	F	MB
	Health and safety					
	Contractor 1	**Contractor 2**	**Contractor 3**	**Contractor 4**	**Contractor 5**	**Contractor 6**
DM1	B	B	G	G	MB	G
DM2	B	B	MG	G	F	F
DM3	MB	VB	VG	G	MB	G
DM4	MB	EB	VG	VG	MG	G
DM5	F	EB	MG	E	F	F
DM6	B	B	G	G	MG	MG
	Management capability					
	Contractor 1	**Contractor 2**	**Contractor 3**	**Contractor 4**	**Contractor 5**	**Contractor 6**
DM1	F	MG	G	MB	VG	VG
DM2	F	MG	MG	F	VG	VG
DM3	F	MG	MG	F	VG	VG
DM4	MG	F	MG	MB	G	VG
DM5	MG	F	MG	B	G	MG
DM6	MB	MB	G	MB	G	VG

Table 9. Initial IVF decision-making matrix.

Contractor	R	FS	TA	HS	MC
Cont 1	[(4.17, 4.42), 4.92, (5.67, 6.17)]	[(4.83, 5.08), 5.58, (6.33, 6.83)]	[(5.17, 5.42), 5.92, (6.67, 7.17)]	[(2.67, 2.92), 3.42, (4.17, 4.67)]	[(4.17, 4.42), 4.92, (5.67, 6.17)]
Cont 2	[(2.75, 3.25), 3.75, (4.25, 4.75)]	[(6.00, 6.25), 6.75, (7.50, 8.00)]	[(5.50, 5.75), 6.25, (7.00, 7.50)]	[(1.17, 1.42), 1.92, (2.67, 3.17)]	[(4.33, 4.58), 5.08, (5.83, 6.33)]
Cont 3	[(5.75, 6.25), 6.75, (7.25, 7.75)]	[(3.67, 3.92), 4.42, (5.17, 5.67)]	[(3.33, 3.58), 4.08, (4.83, 5.33)]	[(6.00, 6.25), 6.75, (7.50, 8.00)]	[(5.33, 5.58), 6.08, (6.83, 7.33)]
Cont 4	[(2.25, 2.75), 3.25, (3.75, 4.25)]	[(6.17, 6.42), 6.92, (7.67, 8.17)]	[(1.33, 1.58), 2.08, (2.83, 3.33)]	[(6.50, 6.75), 7.25, (8.00, 8.50)]	[(3.17, 3.42), 3.92, (4.67, 5.17)]
Cont 5	[(6.42, 6.92), 7.42, (7.92, 8.42)]	[(3.67, 3.92), 4.42, (5.17, 5.67)]	[(4.67, 4.92), 5.42, (6.17, 6.67)]	[(4.00, 4.25), 4.75, (5.50, 6.00)]	[(6.50, 6.75), 7.25, (8.00, 8.50)]
Cont 6	[(0.42, 0.92), 1.42, (1.92, 2.42)]	[(6.67, 6.92), 7.42, (8.17, 8.67)]	[(3.00, 3.25), 3.75, (4.50, 5.00)]	[(5.17, 5.42), 5.92, (6.67, 7.17)]	[(6.67, 6.92), 7.42, (8.17, 8.67)]

Table 10. Normalized IVF decision-making matrix.

Contractor	R	FS	TA	HS	MC
Cont 1	[(0.47, 0.50), 0.56, (0.66, 0.72)]	[(0.23, 0.28), 0.38, (0.53, 0.63)]	[(0.62, 0.66), 0.74, (0.86, 0.95)]	[(0.20, 0.24), 0.31, (0.41, 0.48)]	[(0.18, 0.23), 0.32, (0.45, 0.55)]
Cont 2	[(0.29, 0.35), 0.42, (0.48, 0.54)]	[(0.47, 0.52), 0.62, (0.77, 0.87)]	[(0.68, 0.72), 0.80, (0.92, 1.00)]	[(0.00, 0.03), 0.10, (0.20, 0.27)]	[(0.21, 0.26), 0.35, (0.48, 0.58)]
Cont 3	[(0.67, 0.73), 0.79, (0.85, 0.92)]	[(0.00, 0.05), 0.15, (0.30, 0.40)]	[(0.32, 0.36), 0.45, (0.57, 0.65)]	[(0.66, 0.69), 0.76, (0.86, 0.93)]	[(0.39, 0.44), 0.53, (0.67, 0.76)]
Cont 4	[(0.23, 0.29), 0.35, (0.42, 0.48)]	[(0.50, 0.55), 0.65, (0.80, 0.90)]	[(0.00, 0.04), 0.12, (0.24, 0.32)]	[(0.73, 0.76), 0.83, (0.93, 1.00)]	[(0.00, 0.05), 0.14, (0.27, 0.36)]
Cont 5	[(0.75, 0.81), 0.88, (0.94, 1.00)]	[(0.00, 0.05), 0.15, (0.30, 0.40)]	[(0.54, 0.58), 0.66, (0.78, 0.86)]	[(0.39, 0.42), 0.49, (0.59, 0.66)]	[(0.61, 0.65), 0.74, (0.88, 0.97)]
Cont 6	[(0.00, 0.06), 0.13, (0.19, 0.25)]	[(0.60, 0.65), 0.75, (0.90, 1.00)]	[(0.27, 0.31), 0.39, (0.51, 0.59)]	[(0.55, 0.58), 0.65, (0.75, 0.82)]	[(0.64, 0.68), 0.77, (0.91, 1.00)]

Table 11 displays the outcomes of the computation of S_i and P_i vectors for the upper and lower bounds using the weights obtained from the previous phase and Equations (21)–(24).

Table 12 illustrates the K coefficient values obtained using Equations (25)–(33) and $\lambda = 0.5$. As shown in Table 13, Contractor 5 is ranked as the best alternative, whereas Contractor 4 is regarded as the worst alternative. The reliability of this approach can be affirmed by comparing the ranking produced by each value of K_{ia}, K_{ib}, K_{ia} and the final K_i value. It is observed that the final ranking and each individual ranking are in agreement, indicating a high level of consistency. Therefore, the evaluation decision for the contractor selection problem is as follows:

$$5 \succ 6 \succ 3 \succ 1 \succ 2 \succ 4 \tag{34}$$

Table 11. The computation of S_i and P_i vectors.

Contractor	S_i^l	S_i^u	P_i^l	P_i^u
Contractor 1	0.493	0.529	4.276	4.301
Contractor 2	0.480	0.515	4.159	3.989
Contractor 3	0.575	0.610	4.377	4.149
Contractor 4	0.389	0.424	3.925	3.650
Contractor 5	0.649	0.685	4.482	4.255
Contractor 6	0.580	0.616	4.350	4.140

Table 12. The computation of K_i.

Contractor	K^l_{ia}	K^u_{ia}	K^l_{ib}	K^u_{ib}	K^l_{ic}	K^u_{ic}
Contractor 1	0.166	0.173	2.356	2.428	0.929	0.969
Contractor 2	0.161	0.162	2.293	2.308	0.904	0.903
Contractor 3	0.172	0.171	2.591	2.577	0.965	0.954
Contractor 4	0.150	0.146	2.000	2.000	0.841	0.817
Contractor 5	0.179	0.177	2.810	2.784	1.000	0.991
Contractor 6	0.172	0.171	2.598	2.588	0.961	0.954

Table 13. The ranking results.

Contractors	K^l_i	K^u_i	K_i	Rank
Contractor 1	1.864	1.931	1.898	4
Contractor 2	1.814	1.820	1.817	5
Contractor 3	1.998	1.983	1.991	3
Contractor 4	1.629	1.608	1.619	6
Contractor 5	2.124	2.105	2.115	1
Contractor 6	1.997	1.987	1.992	2

6. Result Discussion and Sensitivity Analysis

6.1. Result Discussion

Firstly, as can be seen in Figure 3, Contractor 5 achieved the highest rank with a mean score of 2.115, indicating that they have performed the best overall. Additionally, Contractor 6 has achieved the second-highest rank with a mean score of 1.992, whereas Contractor 3 has achieved the third-highest rank with a mean score of 1.991. On the other end of the spectrum, Contractor 4 has achieved the lowest rank with a mean score of 1.619, indicating that they have performed the worst overall. Additionally, Contractor 2 has achieved the second-lowest rank with a mean score of 1.817.

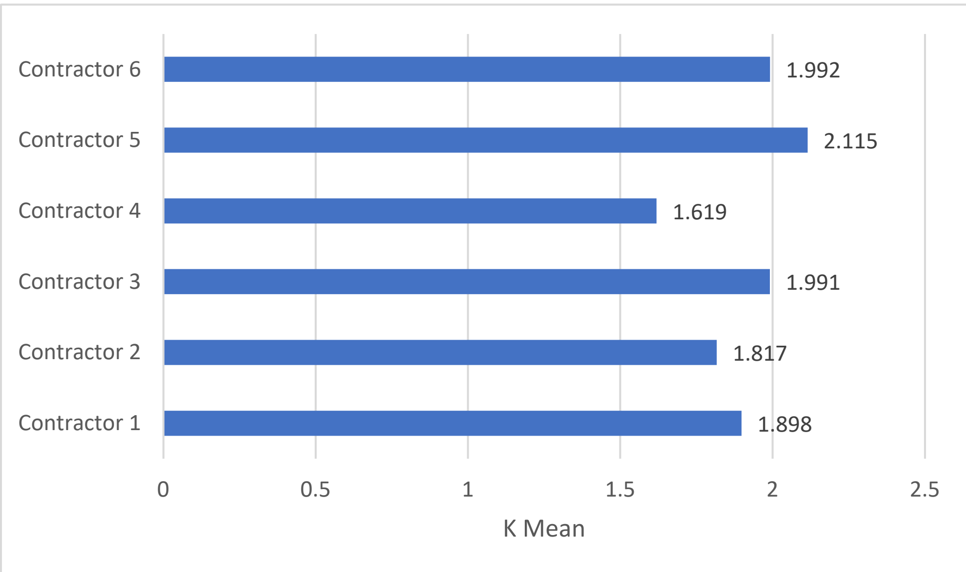

Figure 3. The mean score achieved by each contractor.

It is also important to note the range of scores for each contractor, as indicated by their upper and lower confidence intervals. For example, Contractor 5 has a relatively narrow confidence interval, with a range of only 0.019 between their upper and lower bounds. This indicates a high degree of confidence in the accuracy of their mean score. In contrast, Contractor 4 has a much wider confidence interval, with a range of 0.021, indicating that there is more uncertainty in their mean score.

One important consideration when interpreting these results is the size of the differences between the mean scores of each contractor. For example, although Contractor 5 had the highest mean score, the difference between their score and that of Contractor 6 is relatively small, at only 0.123. On the other hand, the difference between the mean score of Contractor 5 and that of Contractor 1 (who achieved the fourth-highest rank) is much larger, at 0.217.

It is also worth noting that the confidence intervals for Contractors 1, 3, and 6 all overlap, indicating that there is not a significant difference in their mean scores. In contrast, the confidence intervals for Contractors 2 and 4 do not overlap with those of any other contractors, indicating that their mean scores are significantly different from the others.

Looking at the rankings, it is interesting to note that the contractor with the highest mean score (Contractor 5) also had the highest scores for management capability, which was the most important criterion. This suggests that this factor played a key role in its overall performance.

Another consideration when interpreting these results is the potential impact of outliers or extreme values. If any individual data points were significantly higher or lower than the others for a particular contractor, it could skew their overall mean score and potentially impact their rank. It would be important to carefully review the data to ensure that there were no such outliers or anomalies that could be distorting the results.

Furthermore, there are other factors that could affect the interpretation of these results. For example, it is important to consider whether all contractors had the same scope of work or were given the same resources and timelines to complete their tasks. If there were differences in these factors, it could impact the validity of the comparison between contractors.

It is worth considering whether the evaluation criteria used to assess the contractors were comprehensive and relevant to the project goals. If the criteria did not fully capture all aspects of the project's success, it could lead to an incomplete or biased assessment.

In essence, although the average scores and rankings can offer valuable insight into the contractor's performance, it is vital to consider the supplementary factors and constraints when interpreting the outcomes.

6.2. Sensitivity Analysis

A sensitivity analysis is a crucial tool that helps decision-makers to evaluate the reliability of their decision-making process. By testing the primary model with various changes, decision-makers can identify the robustness of their approach and ensure that their decisions are well-informed and well-founded. In this study, we performed a randomly generated weight replacement strategy to conduct a sensitivity analysis, which included 40 different tests to exchange the weights of criteria and determine corresponding alternative ranks. The tests were designed to demonstrate the accuracy and deviation of decision outcomes, as well as to justify the obtained results.

Table 14 presents the results of the sensitivity analysis, including the 40 possible tests for weights sensitivity analysis. As seen in Figure 4, the analysis showed that Contractor 5 was ranked as the top alternative in 31 of the tests, indicating that it is the best alternative. This finding provides decision-makers with a high level of confidence that Contractor 5 is the most suitable contractor for the task at hand.

Moreover, the sensitivity analysis also identified Contractor 4 as the least important item, as it ranked last in 26 tests. This information can be used by decision-makers to allocate resources more effectively and prioritize tasks that are more critical to the project's success. Based on the observations depicted in Figures 5 and 6, it is evident that when the reputation criterion is not included among the two most significant criteria, Contractor 5 fails to secure the top position in the rankings. Notably, in 23 out of the 31 instances where Contractor 5 was identified as the optimal choice, the reputation criterion was placed as the most pivotal consideration. These findings imply that the reputation criterion is a vital determinant for selecting Contractor 5.

Table 14. Ranking of contractors in each of the 40 tests of sensitivity analysis.

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

Moreover, irrespective of the weights assigned to the criteria, neither Contractor 1 nor Contractor 5 were ever placed at the bottom of the rankings. This indicates that both contractors consistently demonstrated satisfactory performance across all criteria evaluated. While the ranking of contractors 1, 2, and 6 is highly dependent on the configuration of the evaluation criteria, suggesting a fluctuating performance across various criteria for these contractors.

In conclusion, the sensitivity analysis performed in this study provides decision-makers with valuable insights into the ranking of alternative contractors. By testing the model with different weight combinations, decision-makers can identify the robustness and reliability of their approach, ultimately leading to well-informed and well-founded decisions. The results of this study highlight the superiority of Contractor 5 over other alternatives.

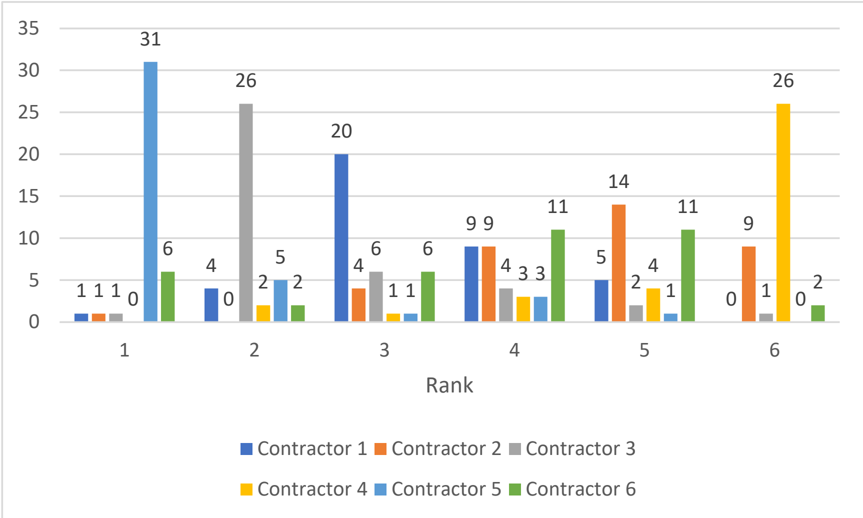

Figure 4. The rankings achieved by each contractor based on the results of 40 tests.

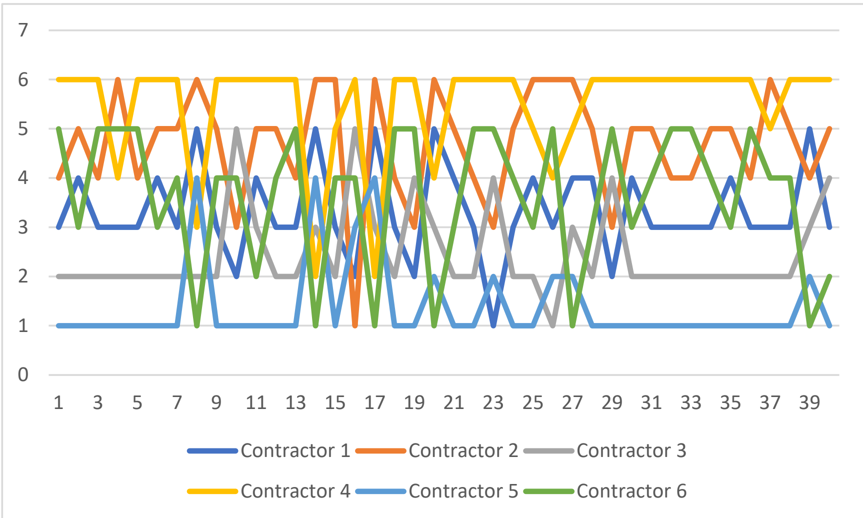

Figure 5. Performance of each contractor in 40 tests of sensitivity analysis.

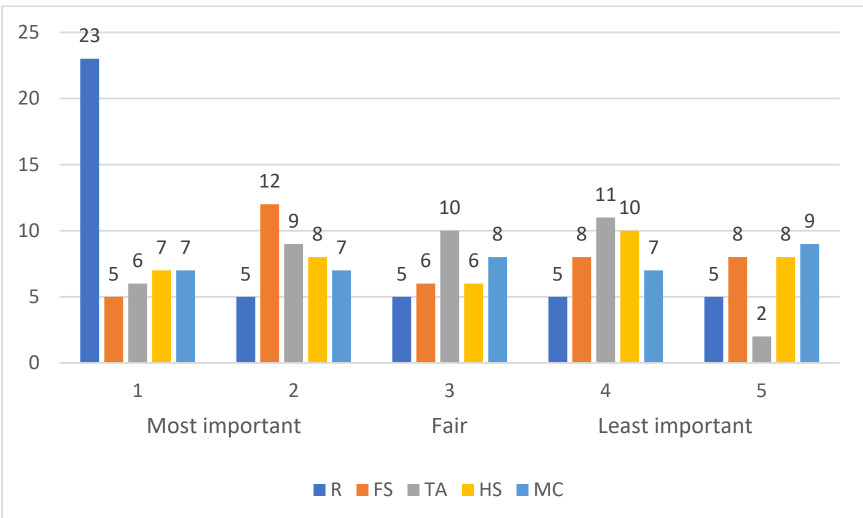

Figure 6. Importance of each criterion in 40 tests of sensitivity analysis.

7. Conclusions

To sum up, as the construction industry continues to evolve, the need for effective contractor selection methods becomes even more crucial. In this study, we have proposed the IVF-SWARA and IVF-CoCoSo methods as comprehensive frameworks for contractor selection based on multiple criteria, providing decision-makers with a reliable and effective solution. By applying these methods to a numerical example, we have demonstrated their practical application and effectiveness in contractor selection. The results obtained from the application of the proposed methods have shown promising outcomes, validating their potential to aid in the decision-making process for project managers and stakeholders.

Moreover, the sensitivity analysis conducted in this study has provided valuable insights into the impact of various criteria weights on the final ranking of contractors. This analysis has showcased the adaptability and flexibility of the proposed methods, allowing decision-makers to adjust their criteria preferences and understand the implications on contractor selection.

Looking ahead, there are several avenues for future research in this field. Firstly, expanding the scope of criteria considered in the contractor selection process would enhance the comprehensiveness of the proposed methods. Additionally, conducting empirical studies involving real-world construction projects would further validate the effectiveness and applicability of these methods in practical scenarios. Furthermore, to enhance the precision and robustness of the contractor selection process, future research can explore the utilization of newer concepts of fuzzy set theory, such as Interval Type-2 Fuzzy Numbers (IT2FNs). IT2FNs provide a higher degree of flexibility in representing uncertainty and vagueness in decision-making. By incorporating IT2FNs into the contractor selection framework, decision-makers can effectively handle imprecise and uncertain information, leading to more accurate and reliable evaluations of contractors. The use of IT2FNs can enable a more comprehensive analysis of contractor performance across various criteria, considering the inherent fuzziness present in real-world construction projects.

In conclusion, the IVF-SWARA and IVF-CoCoSo methods presented in this study provide a structured and systematic approach to contractor selection. The practical application, along with the results obtained and the insights gained from the sensitivity analysis, supports their reliability and effectiveness. By utilizing these methods, project managers and stakeholders can make informed decisions and increase the likelihood of achieving project success. Future research endeavors can build upon these foundations to further enhance the contractor selection process and integrate new technologies for improved decision-making capabilities. In addition, to handle high uncertainty in the real-world applications, new extended fuzzy sets, such as type-2 fuzzy sets, interval-valued intuitionistic fuzzy sets, and interval-valued Pythagorean fuzzy sets, can be taken from the recent literature [44–50].

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