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A Hybrid TOPSIS-Structure Entropy Weight Group Subcontractor Selection Model for Large Construction Companies

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Abstract: The selection of suitable subcontractors for large construction companies is crucially important for the overall success of their projects. As the construction industry advances, a growing number of criteria need to be considered in the subcontractor selection process than simply considering the bidding prices. This paper proposed a hybrid multi-criteria structure entropy weight (SEW)—TOPSIS group decision-making model that considers 10 criteria. The proposed model was able to handle large amount of subcontractors' performance data that were collected in different types. Additionally, the model can integrate experts' judgments while accounting for their varying level of expertise and correcting for their biases. This paper also provided a case study to demonstrate the proposed model's effectiveness and efficiency, as well as its applicability of large construction companies. While this study was applied to construction subcontractors' selection, the proposed methodology can also be easily extended to various decision-making scenarios with similar requirements.

Keywords: construction subcontractor; big data; hybrid multi-attributes; group decision-making; TOPSIS; structure entropy method



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1. Introduction

Subcontracting is a process in which a general contractor subcontracts some parts of the work to another contractor. Construction subcontractors help general contractors overcome problems related to the need for special expertise, shortage in resources, and limitation in finances. At present, construction subcontractors handle about 85% of all construction projects in the building industry and this trend is expected to continue in the future [1,2]. The success of construction projects is highly susceptible to the performance of the subcontractors. Therefore, selecting the most appropriate subcontractors is very critical for overall project success [3–5].

A construction project which lacks an effective subcontractor selection process is prone to many serious problems such as time and cost overruns, substandard work, disputes, and dissatisfaction of the clients. An ineffective subcontractor selection process may also lead to qualified construction subcontractors going out of business if subcontractors are only selected based on cost, which will ultimately reduce the quality of construction [6]. In the past, construction subcontractors were mostly selected based on the lowest bid price [7]. The process of selecting subcontractors based on the lowest bid may seem easy, but many factors makes it complicated. The majority of subcontractors' bids are often phoned or faxed into the general contractor's office at the last minute, because of the subcontractors' fear that the contractor will engage in bid shopping. Bid shopping is the practice of revealing a subcontractor's bid to other prospective subcontractor(s) before the award of a subcontract in order to secure a lower bid. This short period of time does not

allow the amount of analysis desired for optimal subcontractors' selection particularly if a sound selection process is not in place.

The number of subcontract bids received in a short amount of time can be overwhelming for both large and small construction companies. However, other factors make the subcontractors' selection process even more complicated for large companies because of the difference in available information and size. Compared with small construction companies, large ones invested heavily in information technology. They have access to building information modeling tools on site, which are typically beyond the financial capabilities of small companies. The large companies' superintendents and project managers have access to tablets in the field that allow them to collect massive amount of data and information including actual cost and schedule, daily reports, meeting minutes, opinions, and surveys and pictures documenting subcontractors' performance. Such information can be referred to as big data, and is constantly being acquired and stored in the company's historical database and has the potential of significantly improving decision making, if used effectively [8]. Big data can come from people, computers, machines, sensors, and any other data-generating device or agent [9]. It is important to note that when considering the potential of big data for improving decision-making, it is not the amount of data that is important but rather what companies do with all the data. It is, therefore, important to develop models that can effectively use the data, such as the model proposed in this paper.

In addition to having access to significantly more data, large firms employ a large number of project managers and project executives with a significant combined experience that can deal with a variety of projects and solve many technical issues that may arise. Furthermore, the large number of project managers and executives have experiences working with an even larger number of subcontractors. Such an experience can offer a significant competitive advantage to the company if captured effectively in the company's system and used when selecting subcontractors for future projects. On the other hand, in case of small firms, the owner of the firm in many cases is the project manager and he/she typically worked with a limited number of subcontractors and usually does not have access to extensive technology tools to collect vast amount of information on subcontractors' performance. As a result, in the case of small firms, the subcontractors' selection process is less data-intensive and typically depends on one individual. For these reasons, the authors recommend that the subcontractor selection process used by large construction firms should be different from that used by smaller firms.

To be effective, the process used by large construction companies for selecting subcontractors should include several different attributes. These include (1) the ability to provide timely recommendations, (2) the ability to deal with a growing amount of big data and growing number of selection criteria, and (3) the ability to integrate experts' opinions and judgments in a manner that accounts for their varying level of knowledge and experience. To realize such process, this paper proposed a hybrid multi-criteria structure entropy weight (SEW)—TOPSIS (technique for order preference by similarity to an ideal solution) group decision-making model. In the proposed model, the structure entropy weight method was used to calculate the weights of the selection criteria based on experts' judgments while offsetting the uncertainties associated with their judgements. The method of minimum deviation was then used to determine the weights of experts' opinions to account for their varying level of expertise and knowledge. Finally, TOPSIS was used to rank and select the most suitable construction subcontractor. An illustrative example was used to demonstrate the feasibility of the proposed model.

The proposed model can utilize a large amount of subcontractors' performance data collected in different formats, and it was able to handle multiple criteria and calculate the weights to the various criteria in a speedy manner. It can also integrate experts' judgments while accounting for their varying level of expertise and correcting for their biases.

In the remainder of the paper, a literature review of previous studies related to subcontractor selection is presented. Then, the criteria used for subcontractors' selection in

the proposed model are discussed. Lastly, the paper describes the development of the proposed model and presents a case study to illustrate how the model is applied.

2. Literature Review

In the past, construction subcontractors were mostly selected based on the lowest bid price [7]. A selection based on the lowest bid could cause immense additional costs in the long run due to deficient quality of work and the resulting cost of rework, additional cost of supervision, preponderance of claims, disputes and adversarial relationships, and, in worst cases, abandonment of work or bankruptcy. Therefore, the optimal selection of construction subcontractors based on overall ability to perform, rather than on tender price alone, is crucial to a successful project delivery.

The literature review suggests that because of the importance of selecting quality subcontractors, previous research was conducted to aid general contractors in their subcontractors' selection process. Several studies developed multiple-criteria decision-making MCDM models that also included a weighted score to help evaluate additional criteria other than using price alone [1,2,4].

Arslan et al. [10] proposed a simplified web-based sub-contractor evaluation system called WEBSES to evaluate construction subcontractors based on multiple criteria. They claimed that WEBSES eliminates the dependence on the lowest bid price by considering combined criteria, which can speed up the subcontracting process, improve the quality of decision-making and reduce costs of the selection process. Zavadskas et al. [11] proposed a multi-attribute selection model that optimally select subcontractors according to the Hodges–Lehmann rule. They stated that their model reduced the risk involved in the selection phase and eliminated unqualified contractors during the bidding process. Mbachu [1] developed a conceptual framework for the assessment of construction subcontractors' eligibility and performance. He first investigated the criteria used to assess subcontractors' eligibility for bid invitation and award and then investigated the criteria used to assess the subcontractor's performance during the construction phase. He concluded that the quality of work is the most influential criterion for shortlisting construction subcontractors for bid invitation. He determined that bid items' prices and total bid price were the most influential criteria for awarding a subcontract. He also determined that the construction subcontractors' quality of work is the most influential criterion used to assess the subcontractor's performance during the construction phase. El-Mashaleh [12] proposed a data envelopment analysis model for selecting construction subcontractors. He claimed that his proposed model can be tailored to reflect any general contractors' criteria for construction subcontractor selection. Ulubeyli and Kazaz [6] developed a construction subcontractor selection model based on fuzzy multi-criteria decision-making. They were able to model human judgments using linguistic terms and combined qualitative and quantitative decision criteria into an aggregate measure. They claimed that the proposed model can choose the most suitable construction subcontractor for a specific project rather than the "best" subcontracting firm in absolute terms. Demirkesen and Bayhan developed a choosing-by-advantages (CBA) construction subcontractor selection method based on various criteria such as past performances, innovation capacity, and current workload. In their study, they emphasized the importance of having a multi-criteria evaluation system that reduces the chance of omitting any construction subcontractor's advantage [2].

It needs to be mentioned that as techniques advance in the construction industry, the active BIM approach was also used in subcontracting and subcontractor selection applications. Sadeh et al. conducted an investigation of BIM feasibility for small and medium-sized contractors and subcontractors (SMEs), and found that SMEs have both cultural and technological lag in implementing new technologies, which limited their further applications [13]. Jang et al. proposed a two-step subcontracting process for building information modeling (BIM)-based design coordination under a design-bid-build (DBB) contract that focusing on cost reduction and project delivery efficiency (Jang et al., 2019) [14]. Sun et al. conducted research on BIM application in EPC projects regarding

cooperation between owners and general contractors to reduce costs and increase efficiency. These studies indicate that subcontractors, especially the small ones, tend to use the active BIM approach less, and even when they did use it, the main focus was mostly about costs and time (Sun et al., 2021) [15].

Previous studies listed above significantly improved the subcontractor selection process. Many existing models presented by past studies, however, are not capable of dealing with a growing number of selection criteria that are measured using different data types (e.g., precise numeric, numerical range, and linguistic variable). In addition, in most reviewed studies, the selection of construction subcontractors was treated as a multi-attribute, but single expert decision-making process, which did not recognize and incorporate the advantages of group decision-making. Each expert has his/her own experiences and specialty that can have significant subjective influence on the decisions they make in the subcontractor selection process. Thus, the appropriate implementation of the hybrid multi-attributes group decision-making model as proposed in this paper is advantageous in the way of being able to select and integrate different attributes and experts in the evaluation of construction projects' subcontractors.

Recently, Taylan et al. [8] proposed a group decision-making model for the selection of contractors using big data. In their paper, they first made the case for why the use of big data for contractor selection is significantly more advantageous than relying on tender price alone. They then proposed a hybrid model that combined two different methods for selecting contractors using fuzzy and numerical data. Their proposed hybrid model initially used Fuzzy AHP to determine the weights of criteria. Then, it used fuzzy TOPSIS to select the most appropriate contractor. Drawing from the work of Taylan et al. [8], we attempted to further improve the process of selecting contractors using big data by proposing a model that can handle more data types (i.e., precise numbers, numerical ranges, and linguistic terms) and that use the structure entropy method to determine the weights of the decision criteria. It was important to develop a model that can handle numerical ranges to be able to consider important criteria, such as historical cost and schedule overrun experienced by subcontractors on their previous jobs. The inclusion of such data is important, since a vital goal of subcontractor selection should be one that reduces uncertainty/risk, and capturing variability of past performance is, thus, necessary. In the proposed model, a subcontractor's historical cost overrun was expressed as a numerical range of the ratios of the subcontractor's final price to the bid price from previous jobs. For example, a range of [0.95,1.3] means that on previous jobs, a subcontractor's final price with subcontractor's initiated change orders varied from being as low as 95% to as high as 130% of the original subcontract price.

It can be learned from the literature review that this paper adds to previous work by introducing a novel hybrid model, which provides a broader evaluation perspective to enhance subcontractor selection effectiveness for large construction companies. The main advantages of the proposed model for subcontractor selection are as follows:

- Capable of making appropriate selection in a timely manner since, as discussed above, the majority of the subcontract bids are submitted within a few hours of the bid deadline;
- Can be easily implemented using a spreadsheet;
- Capable of using data in different types (e.g., precise numbers, numerical ranges, and linguistic terms) which is also large in the amount;
- Capable of handling multiple criteria. Both the number of criteria and the amount of data available often increase while large construction companies continue to improve their abilities to digging information from the big data they keep collecting;
- Capable of identifying the relative weights of the selection criteria;
- Capable of integrating experts' knowledge and experiences;
- Capable of correcting for biases and uncertainties associated with experts' judgements;
- Capable of properly giving weights to experts based on their level of expertise and experience.

3. Determination of Criteria for Construction Subcontractor Selection

Through a literature review and interviews with experts, a total of 10 frequently used criteria for subcontractor selection were selected for the purpose of constructing the proposed model, and are further discussed below.

- (1) **Price:** This criterion is measured using a precise number representing the bid price that the subcontractor submits to the general contractor. Since general contractors aim to maximize their profits, they typically tend to choose subcontractors who submit the lowest prices. This criterion was used by many previous studies [4,7,16].
- (2) **Safety:** Concerns about the safety of construction workers dramatically increased recently [17]. For this reason, more general contractors are evaluating their subcontractors based on their safety performance. The experience modification ratio (EMR) is one way of measuring safety performance. The EMR reflects the history of workers' compensation losses from accidents that a construction subcontractor endured compared to other employers in the same industry. The EMR is expressed as a precise number where a rating of 1.0 represents the industry average. Companies with good safety records have a low EMR. This criterion was used in many previous studies [18–21].
- (3) **Amount of sub-subcontracts:** This criterion is measured using a precise number representing the % of work that is further subcontracted by the subcontractor. It is common for subcontractors to hire other sub-subcontractors. This is often referred to as multi-tier subcontracting. Multi-tier subcontracting may be necessary when projects require specialized skills, but often companies use it to pay lower wages and eliminate employee benefits. A major criticism of multi-tier subcontracting is insufficient pay, since each tier of subcontractor takes a portion of the payments for the subcontracted work, with the worker actually performing the task often getting insufficient pay. Another criticism of multi-tier subcontracting is that employers sometimes pressure workers to become "independent" contractors rather than employees. This allows employers to shift operating costs and responsibility for compliance with labor laws to the workers themselves which in many cases create dangerous working conditions. For the above reasons, many general contractors prefer subcontractors who limit the use of multi-tier subcontracting to work requiring specialized skill. This criterion was used by Abbasianjahromi et al., 2014 [22].
- (4) **Cost overrun:** Staying on budget is one of the key success factors of construction projects [23]. Cost overrun leads to adversarial relationships among owners, contractors, and subcontractors. Cost overrun on past projects reflects the subcontractor's cost control capabilities and is measured in this study using a numerical interval that represents the range of bid price to final price on past projects completed by the subcontractor. For example, a subcontractor's "cost overrun" that is equal to [1.1–1.5] means that the past projects of this subcontractor ended up 10 to 50% more expensive than the bid price. This criterion was used previously by Sönmez et al. [20,21].
- (5) **Schedule overrun:** Staying on schedule is another key success factor of construction projects [24]. Schedule overrun results in higher project overhead costs and during inflationary periods may lead to higher material and labor costs [25]. In this paper, schedule overrun was also measured using a numerical interval that represents the range of estimated project duration in days to final actual duration on past projects completed by the subcontractor. For example, a subcontractor's "schedule overrun" that is equal to [0.95–1.1] means that the past projects of this subcontractor ended up 5% shorter to 10% longer than estimated and proposed. This criterion was used previously by Sönmez et al. [20,21].
- (6) **Quality of work:** Quality is also a key construction project success factor [17,24,26]. Achieved quality on past projects reflects a subcontractor's ability to satisfy owners' needs as defined in the specifications and to provide adequate quality of service [27]. This criterion is often measured using linguistic terms such as "very good" or "very poor". This criterion was used previously by Hartmann et al. and Marzouk et al. [7,21].

- (7) Experience with similar projects: During the bidding process, general contractors may receive bids from unknown subcontractors. One way for a general contractor to reduce risks associated with unknown subcontractors is to select a subcontractor who has experience with similar projects and/or who is familiar with the location of the project to be constructed, local labor laws, and/or local material suppliers. In this paper, a subcontractor's "experience with similar projects" was measured using linguistic terms that represent experts' judgments of the past experiences of the subcontractor after reviewing the subcontractors' technical proposals. This criterion was used previously by Sönmez et al. [20]; and Marzouk et al. [21].
- (8) Past relationship with general contractor: General contractors are more inclined to select subcontractors who successfully worked with them before, because they can more easily build trust. In this paper, a subcontractor's "past relationship with general contractor" was also measured based on experts' judgements using linguistic terms. This criterion was used previously by Hartmann et al. [7].
- (9) Technical competence: Subcontractors are hired to perform specific work and consequently need to possess certain technical knowledge to undertake the work. Technical competence refers to the "know-how" that the subcontractor provides and includes patented technology, advanced equipment, and knowledge of building codes' requirements [28]. In this paper, a subcontractor's "technical competence" was measured using linguistic terms that represents the experts' views about the past experiences of the subcontractor after reviewing the subcontractors' technical proposals. This criterion was used previously by Hartmann et al. [7].
- (10) Management competence: Since subcontractors have to collaborate with other subcontractors on a construction project, they should possess strong management competencies that include effective communication and coordination skills. In this paper, a subcontractor's "management competence" was also measured based on experts' judgements using linguistic terms. This criterion was used previously by Sönmez et al. [20] and Marzouk et al. [21].

4. A Hybrid Multi-Criteria Group Decision-Making Model for Construction Subcontractor Selection

4.1. Method Selection

Because the selection of construction subcontractors often involves comparing strengths and weaknesses of multiple construction subcontractors, it is difficult for a single decision maker to determine the best choice. To improve the effectiveness and efficiency of construction subcontractor selection, experts from different domains are often gathered to increase the objectivity of the final decision. Meanwhile, due to the knowledge structures, personal preferences, and professional limitations of the decision makers and the vagueness and uncertainties of the evaluation criteria, group decision experts often have difficulty of using precise numbers to appraise all evaluation criteria; instead, they tend to choose interval numbers, linguistic terms, or fuzzy numbers for the evaluation. Among the different types of criteria used in the construction subcontractor selection process, some can be evaluated quantitatively by precise numbers. Examples of such criteria are "price", "experience modification ratio", "amount of subcontracts". Other criteria such as "cost overrun" and "schedule overruns" are measured using numerical intervals. Other criteria are qualitative and are measured using linguistic terms. Examples of such qualitative criteria include "quality of work", "experience with similar projects", "past relationship with general contractor", "technical competence", and "management competence." To be able to aggregate all the criteria that are measured using different data types, it is necessary to convert the mixed data information into precise numbers. In this paper, the continuous ordered weighted averaging (COWA) operator was used to convert numerical intervals while a defuzzification method was used to convert the trapezoidal fuzzy numbers utilized for measuring qualitative criteria. The structure of the proposed model is shown in Figure 1.

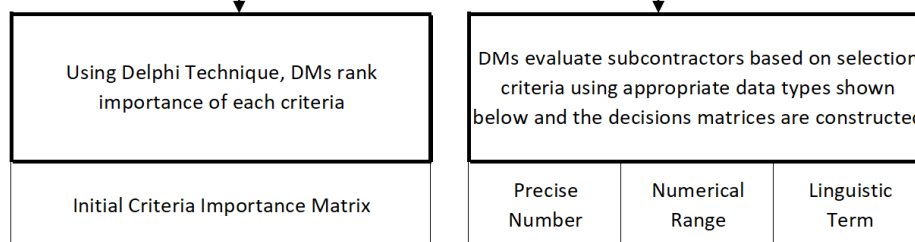
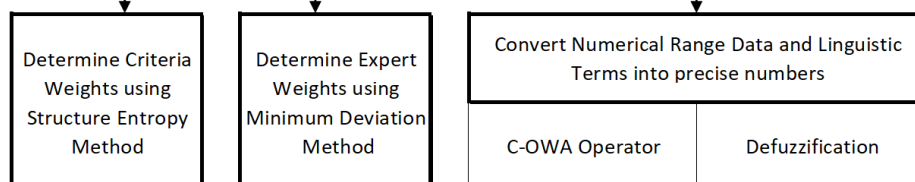
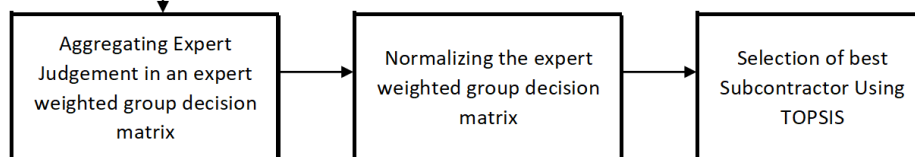
Phase I: Process Setup**Phase II: Big Data Collection****Phase III: Determine Criteria and Expert Weight and Transform Evaluation Data****Phase IV: Subcontractor Selection using TOPSIS**

Figure 1. Scheme of the proposal model of the Hybrid Multi-Criteria Group Decision-making.

In the proposed model, it is necessary to properly determine the weights of the selection criteria and the experts. For the criteria's weights, the proposed model uses the structure entropy weight method (SEWM) which combines subjective and objective weight determination methods to reduce the error from subjective factors and increase reliability. Compared to AHP, SEWM can reduce a large amount of the computational workload and obtain more accurate results in the case of a large number of evaluation criteria. For the experts' weights, the method of minimum deviation based on the consistency of experts' opinions is used.

Finally, the proposed model uses technique for order of preference by similarity to ideal solution (TOPSIS) to rank all the subcontractors. TOPSIS is a compensatory multi-criteria decision analysis method that compares a set of alternatives by identifying weights for each criterion, normalizing scores for each criterion and calculating the geometric distance between each alternative and the ideal alternative. Compensatory methods such as TOPSIS allow trade-offs between criteria, where a poor result in one criterion (e.g., tender price) can be negated by a good result in another criterion (e.g., historical cost overrun). This provides a more realistic form of modelling than non-compensatory methods, which include or exclude alternative solutions based on hard cut-offs [29]. TOPSIS has many advantages, including broad applications, simple calculations, and full utilization of information in the decision-making matrix [30,31]. Because of these advantages, many construction researchers utilized TOPSIS for various construction decision-making applications [32,33].

4.2. Description of the Various Data Types and How They Are Handled by the Model

The proposed hybrid multi-attribute group decision-making model allows decision makers to provide their evaluation results in the form of precise numbers, numerical ranges, fuzzy numbers, and linguistic terms (i.e., good, poor, etc.). In the proposed model, the precise numbers can only be positive. The following subsections provide more detail on the numerical range, fuzzy numbers, and linguistic terms data types and how they are converted to precise numbers to enable their use by the model.

(1) Numerical range

Let R be the real numbers set, the closed interval $\tilde{a} = [a^-, a^+]$ refers to the numerical range where, $a^-, a^+ \in R$ and $a^- \leq a^+$. In particular, when $0 < a^- \leq a^+$, $\tilde{a} = [a^-, a^+]$ is a positive numerical range; when $a^- = a^+$, $\tilde{a} = [a^-, a^+]$ is degenerated into a precise number.

(2) Trapezoidal Fuzzy Numbers (TFNs)

Fuzzy numbers include triangular fuzzy numbers and trapezoidal fuzzy numbers. Trapezoidal fuzzy numbers consider the most pessimistic, the most probable, and the most optimistic estimates of the evaluation attributes, and they can fully reflect the uncertainty of the judgement. The proposed model utilizes trapezoidal fuzzy numbers.

Let $\tilde{A} = (a, b, c, d)$ be a trapezoidal fuzzy number, where $a, b, c, d \in R$ and $a \leq b \leq c \leq d$, the membership function $\mu_{\tilde{A}} : R \rightarrow [0, 1]$ satisfy the following formula:

$$\mu_{\tilde{A}}(x) = \begin{cases} \frac{x-a}{b-a}, & a \leq x < b \\ 1, & b \leq x \leq c \\ \frac{d-x}{d-c}, & c < x \leq d \\ 0, & \text{others} \end{cases} \quad (1)$$

The membership function $\mu_{\tilde{A}}$ is a linearly increasing function in interval $[a, b]$, which represents the pessimistic estimation of the decision-making experts. The membership function $\mu_{\tilde{A}}$ in interval $[b, c]$ is 1, which represents the most probable estimation of the decision-making experts. The membership function $\mu_{\tilde{A}}$ is a linear decreasing function in interval $[c, d]$, which represents the optimism of the decision-making experts. The membership function $\mu_{\tilde{A}}$ in other regions is 0.

In particular, when $[b = c]$, trapezoidal fuzzy numbers degenerate into triangular fuzzy numbers. In particular, when $[0 < a \leq b \leq c \leq d]$, $\tilde{A} = (a, b, c, d)$ is the positive trapezoidal fuzzy number. a and a are the lower bound and upper bound of $\tilde{A}$, respectively. $d - a$ and $c - b$ represent the fuzzy degree of the trapezoidal fuzzy number, and the larger $d - a$ and $c - b$ are, the more fuzzy degree is.

(3) linguistic fuzzy variables

In the process of group decision-making, it is often difficult to use quantitative numbers to represent certain qualitative attributes, and so, group decision-making experts tend to use linguistic fuzzy terms, such as "high", "medium", and "low" to express their qualitative judgments. An appropriate set of terms need to be defined as shown in Table 1. Since linguistic fuzzy terms cannot be directly manipulated by the model, they need to be quantified and standardized through transformation rules. In the proposed model, the equidistant transformation rules are adopted for transforming the fuzzy linguistic terms into trapezoidal fuzzy numbers, as shown in Table 1 [34].

Table 1. Trapezoidal Fuzzy Numbers Corresponding to the 5-Level Fuzzy Linguistic Term System.

Fuzzy Linguistic Terms	Trapezoidal Fuzzy Numbers
Very High (VH)	(0.857, 1, 1, 1)
High (H)	(0.571, 0.714, 0.857, 1)
Medium (M)	(0.286, 0.429, 0.571, 0.714)
Low (L)	(0, 0.143, 0.286, 0.429)
Very Low (VL)	(0, 0, 0, 0.143)

4.3. Development of the Hybrid Multi-Attributes TOPSIS Group Decision-Making Model

4.3.1. Process Set up

For the selection of construction subcontractors, if there are g subcontractors, represented by $S_k = \{S_1, \dots, S_g\}$ ($k = 1, \dots, g$); m experts participating in the decision-making process represented as $E_i = \{E_1, \dots, E_m\}$ ($i = 1, \dots, m$); and n selection criteria to be evaluated for each subcontractor represented as $U_j = \{U_1, \dots, U_n\}$ ($j = 1, \dots, n$). The weight assigned to selection criterion U_j is ω_j , and the weight assigned to expert E_i is λ_i .

When expert E_i evaluates construction subcontractor S_k based on criterion U_j the value of this evaluation is a_{ij}^k . For the criteria set $U_j = \{U_1, \dots, U_n\}$ ($j = 1, \dots, n$); $A^k = (a_{ij}^k)^T$, all criteria should be classified as either quantitative precise number/numerical range or qualitative criteria. In our case, “Price”, “Experience Modification Ratio”, “Amount of subcontracts” are quantitative and are measured using precise numbers; and “Cost overrun” and “Schedule overruns” are measured using numerical intervals. Qualitative criteria that are measured using linguistic terms include “Quality of work”, “Experience with similar projects”, “Past relationship with general contractor”, “Technical competence”, and “Management competence”. The hybrid decision matrix $A^k = (a_{ij}^k)^T$ is constructed using the values assigned to each selection criteria by each expert for each subcontractor. The number of hybrid decision matrices is the same as the number of subcontractors evaluated. It should be noted that each hybrid decision matrix $A^k = (a_{ij}^k)^T$ contains different types of data (i.e., precise numbers, numerical ranges, and linguistic terms).

4.3.2. Transformation of Data to Numerical Values

As previously stated, it is necessary to convert the data collected as numerical ranges and linguistic terms into precise numbers. The following methods were used for data conversion.

(1) Conversion of numerical ranges

To convert numerical ranges into precise numbers, we used the continuous ordered weighted averaging (COWA) operator proposed by Yager (Yager, 2004) for continuous interval data, as shown below

If $\tilde{a} = [a^-, a^+]$ is the numerical range, then:

$$F_\sigma([a^-, a^+]) \int_0^1 \frac{d\sigma(y)}{dy} (a^+ - y(a^+ - a^-)) dy \quad (2)$$

F_σ is the continuous interval data OWA operator, referred to as “COWA operator”.

If $\sigma(y) = y^\tau$, $\tau \geq 0$, then:

$$F_\sigma([a^-, a^+]) \int_0^1 y^{\tau-1} (a^+ - y(a^+ - a^-)) dy = \frac{a^+ + \tau a^-}{\tau + 1} \quad (3)$$

The value of τ is determined by the decision-making experts. When $0 < \tau < 1$, it means risks are preferred and $\tau = 1$ means a neutral attitude toward risks; If $\tau > 1$, risks

are preferred to be avoided [34]. In this model, because $\tau = 2$, the interval number are converted to a precise number using Equation (4):

$$F_{\sigma}([a^-, a^+]) = \frac{a^+ + 2a^-}{3} \quad (4)$$

(2) Conversion of fuzzy linguistic terms and trapezoidal fuzzy numbers

To convert the fuzzy linguistic terms, Table 1 is first used to convert the fuzzy linguistic terms into trapezoidal fuzzy numbers. Then, the defuzzification method proposed by Chen and Lin [35] is used to convert the trapezoidal fuzzy numbers into precise numbers using Equation (5).

$$d(\tilde{A}) = \frac{a + b + c + d}{4} \quad (5)$$

where $\tilde{A} = (a, b, c, d)$ is a trapezoidal fuzzy number, and $d(\tilde{A})$ is its symbol distance.

Using Equations (4) and (5) and the previously constructed, hybrid decision matrix $A^k = (a_{ij}^k)^T$ as discussed in Section 4.3.1, a converted decision matrix $R^k = (r_{ij}^k)^T$ can be calculated for each subcontractor. Because of the conversion performed as described above, each converted decision matrix contains only precise numbers.

4.3.3. Identifying Criteria Weight by Structure Entropy Weight Method

Properly assigning weights to each criteria is one of the key steps when using MCDM method for subcontractor selection. This assignment can be divided into two methods: subjective methods and objective methods [3,24]. The subjective methods rely on experts' judgements. They include the comparative weighting method, the analytic hierarchy process (AHP), and the Delphi method. For subcontractor selection, AHP was most widely used to calculate the weights of criteria based on input from experts [36,37]. The advantages of using the subjective methods for determining criteria weights are that they fully utilize the experience of experts and their results can be easily explained. However, since their results are based on opinions, they can heavily be influenced by personal biases [24]. In addition, subjective methods such as AHP are often restrained by the human capacity for information processing, and previous studies indicated that the number of criteria handled by such methods should not exceed seven plus or minus [38]. In cases of larger number of criteria, using AHP may not be very accurate and would consume a large amount of experts' valuable time [39].

The objectives methods rely on real data manipulated by various mathematical models. They include the coefficient of variation method, mean square method, entropy weight method, principal component analysis method, and dispersion maximization. Since they rely on data, they ensure the objectivity of the results. However, the results are difficult to explain and, in some cases, will contradict actual situations particularly if the size of the data used is small [24]. The structure entropy weight method (SEWM) used in this research for determining criteria weights integrate subjective and objective weighting methods. Previous studies demonstrated the potential of SEWM in reducing the required calculation workload while increasing the objectivity of the results [39–41]. The SEWM includes several subjective and objective steps: (1) expert opinions are asked to rank the importance of the criteria and an "initial" criteria ranking matrix is created; (2) the entropy method is used to quantitatively analyze the uncertainty associated with experts' opinions (also referred to as blindness) in the "initial" criteria ranking matrix; (3) "blindness" is eliminated and the criteria weights are determined. A detailed explanation of the above steps follows.

(1) Determination of the Initial Criteria Importance Matrix B_{ij} Using Delphi Method

In this step, an expert survey form is created and then sent to a number of experts according to the Delphi method. In the case of subcontractor selection, the experts should be senior project managers and project executives employed by the large construction company. The experts independently rank the importance of each subcontractor selection

criteria in the survey form. The experts should rank the importance of each criterion independently according to their own knowledge and experience. The criteria should be ranked from high to low according to their importance. As shown in Table 2, the most important criterion is assigned a score of “1”, the second most important a score of “2”, etc. Some criteria can be ranked as equally important and assigned the same score [39]. Assume there are m experts and j selection criteria. The ranking of the selection criterion $U_j = \{U_1, \dots, U_n\} (j = 1, \dots, n)$ given by expert E_i is $b_{ij} (i = 1, \dots, m; j = 1, \dots, n)$. The Initial Criteria Ranking Matrix B_{ij} can be created as:

$$B_{ij} = \begin{bmatrix} U_1 & \cdots & U_n \\ E_1 & b_{11} & \cdots & b_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ E_m & b_{m1} & \cdots & b_{mn} \end{bmatrix} \quad (6)$$

Table 2. Scores Assigned to Criteria based on importance.

Importance	Most Important	Second Choice	...	n th Choice
Score	1	2	...	n

(2) Determination of the adjusted criteria Importance Matrix C_{ij} using the structure entropy weight method

The initial criteria importance matrix developed in the previous step based on experts' judgments normally has “data noise” because of the bias introduced by experts. In order to eliminate this noise, the initial criteria importance matrix should be transformed into a more objective adjusted criteria importance matrix using the SWEM. Such transformation is performed using a membership function as follows [39,42]:

$$\mu_{ij} = \frac{\ln(\varepsilon - b_{ij})}{\ln(\varepsilon - 1)} \quad (7)$$

In Formula (7), ε is the conversion coefficient, where $\varepsilon = n + 2$ and n is the number of criteria [42].

The Adjusted criteria importance matrix C_{ij} is:

$$C_{ij} = \begin{bmatrix} U_1 & \cdots & U_n \\ E_1 & \mu_{11} & \cdots & \mu_{1n} \\ \vdots & \vdots & \ddots & \vdots \\ E_m & \mu_{m1} & \cdots & \mu_{mn} \end{bmatrix} \quad (8)$$

(3) Eliminating Blindness and Identifying Criteria Weight Vector W

The adjusted criteria importance matrix could be affected by uncertainties (also referred to as blindness) resulting from experts' biases. It is, therefore, important to eliminate such blindness.

A new parameter “average understanding degree” $\bar{\mu}_j$ is introduced, representing the average of all experts' ranks of each of the criteria, $U_j (j = 1, \dots, n)$, and is calculated as [39]:

$$\bar{\mu}_j = \frac{\mu_{1j} + \cdots + \mu_{mj}}{m} \quad (9)$$

The uncertainty resulting from experts' judgements or blindness q_j is calculated for each criterion as:

$U_j(j = 1, \dots, n)$ is q_j , where

$$q_j = \frac{(\max(\mu_{1j}, \dots, \mu_{mj}) - \bar{\mu}_j) + (\min(\mu_{1j}, \dots, \mu_{mj}) - \bar{\mu}_j)}{2} \quad (10)$$

Then, the adjusted overall ranking Q_j of each criterion $U_j(j = 1, \dots, n)$ provided by the m experts can be calculated as:

$$Q_j = \bar{\mu}_j \times (1 - q_j) \quad (11)$$

The weight ω_j of each criterion $U_j(j = 1, \dots, n)$ is obtained by normalizing:

$$\omega_j = \frac{Q_j}{\sum_{j=1}^n Q_j} \quad (12)$$

Additionally, the overall weight vector of the selection criteria from the group expert decision-making process is $W = (\omega_1, \dots, \omega_n)^T$.

4.3.4. Determination of Experts' Weights Using the Method of Minimum Deviation

When group decision making is used for the selection of subcontractors, the accuracy of the information provided by the experts is very important. If all experts have the same level of experience, they should be assigned the same weight and the decision-making group in such a case is an equal weight decision-making group. However, in most real situations including this case, due to different levels of expertise and knowledge of the experts, the decision-making group should be an unequal weight group and experts' judgments should be weighed differently based on their level of experience [43]. In such cases, it is necessary to determine the weight assigned to each expert.

In this research, the widely utilized minimum deviation method was used to determine the weights of the experts. This method assumes that the closer the rank assigned by an expert to a selection criterion is to the overall rank assigned by all experts, the more weight should be assigned to this expert. To determine the experts' weights using this method, first, the deviations between the ranks assigned to the selection criteria by each expert and those assigned by all experts are calculated. Then, if the difference between the ranks assigned by an expert to the selection criteria and the other experts' assignments is small, this expert is allocated a higher weight.

The process of determining the experts' weights is as follows:

For selection criterion U_j , calculate the deviation D_{ij} between the rank assigned by expert E_i and those assigned by all experts as:

$$D_{ij} = \sum_{i=1}^m (b_{ij} - b_{ij'})^2 \quad (13)$$

where $b_{ij'} = b_{ij}(i' = i = 1, \dots, m; j = 1, \dots, n)$.

Then, calculate the deviation D_i between the ranks assigned by expert E_i and those assigned by all experts to all selection criteria as:

$$D_i = \sum_{j=1}^n \sum_{i=1}^m (b_{ij} - b_{ij'})^2 \quad (14)$$

The following equation is used to allocate a higher weight to an expert having minimum deviation between his/her assigned selection criteria's ranks and those of other experts:

$$\begin{aligned} \min D &= \sum_{i=1}^m \lambda_i^2 D_i \\ \text{s.t. } \sum_{i=1}^m \lambda_i &= 1, \lambda_i > 0, i = 1, \dots, m \end{aligned} \quad (15)$$

By applying Lagrange function to the above equation, we obtain:

$$L(\lambda_i, \theta) = \sum_{i=1}^m \lambda_i^2 D_i + 2\theta \left(\sum_{i=1}^m \lambda_i - 1 \right) \quad (16)$$

By finding the derivatives of λ_i and θ ,

$$\begin{cases} \frac{\partial L}{\partial \lambda_i} = 2\lambda_i D_i + 2\theta = 0 \\ \sum_{i=1}^m \lambda_i = 1 \end{cases} \quad (17)$$

We obtain

$$\lambda_i = \frac{1}{D_i} \frac{1}{\sum_{i=1}^m \frac{1}{D_i}} \quad (18)$$

Additionally, the vector of expert weights is $\lambda = (\lambda_1, \dots, \lambda_m)^T$.

4.3.5. Subcontractor Selection Using TOPSIS

Once the weight of criteria and the weight of experts are known, TOPSIS is used to select the best subcontractor. TOPSIS was first proposed by Hwang and Yoon in 1981 and was widely used for solving multiple criteria decision-making (MCDM) problems. The basic theory of TOPSIS is to find the solution which has the shortest distance from the positive ideal solution (PIS) and the farthest from the negative ideal solution (NIS) in a MCDM problem [44]. The computational procedure in a TOPSIS process is similar to the logic that human uses to make rational decisions. It evaluates unlimited range of criteria with explicit trade-offs and allows compensations between these attributes if any changes happened. Pair-wise comparisons in other methods such as the analytic hierarchy process (AHP) are avoided in TOPSIS. Distance to the PIS and the NIS are taken into consideration at the same time in TOPSIS by defining “relative closeness to ideal solution”. Finally, the ideal solution is selected from the available alternatives by choosing the one that is closest to the PIS and farthest to the NIS is obtained.

To select the best subcontractor using TOPSIS, the experts’ judgments are first aggregated while considering their weights into a group decision matrix which is then normalized before determining the optimal alternative by calculating the distance between each alternative and the ideal alternative. A detailed discussion of the process follows.

(1) *Aggregating experts’ judgement while considering their weights*

The expert weighted group decision matrix X is developed by combining the subcontractor decision matrices $R^k = (r_{ij}^k)^T$ for all of the S_k evaluated subcontractors as determined in Section 4.3.2 and the vector of experts’ weights $\lambda = (\lambda_1, \dots, \lambda_n)^T$ as determined in Section 4.3.4, using the following equation:

$$X_{kj} = \sum_{i=1}^m \lambda_i r_{ij}^k. \quad (19)$$

The expert weighted group decision matrix X can be written as:

$$X = \begin{vmatrix} & U_1 & \cdots & U_n \\ S_1 & X_{11} & \cdots & X_{1n} \\ \vdots & \vdots & \vdots & \vdots \\ S_g & X_{g2} & \cdots & X_{gn} \end{vmatrix} \quad (20)$$

(2) Normalizing the expert weighted group decision matrix

The purpose of normalizing the TOPSIS group decision matrix is to make all scores in the matrix a positive value between 0 and 1. The normalization operation is performed to improve the comparability of the scores assigned to the various selection criteria considered by eliminating the impact of using different units of measurement for each criterion [44].

A few common normalization methods were used [44]. These include vector normalization, linear normalization, and range conversion. In this study, the range conversion method was used. The equations used by the range conversion method depend on whether the criterion being normalized is a “benefit” criterion or a “cost” criterion. A “benefit” criterion is one whose value is preferred to be large. A “cost” criterion is one whose value is preferred to be small. In our proposed subcontractor selection model, the following criteria are of the “cost” type: “Price”, “Experience Modification Ratio”, “Amount of subcontracts”, “Cost overruns”, and “Schedule overruns”. However, the following criteria are of the “benefit” type: “Quality of work”, “Experience with similar projects”, “Past relationship with general contractor”, “Technical competence”, and “Management competence”.

For “benefit” type criteria,

$$Y_{kj} = \frac{x_{kj} - m_k(x_{kj})}{m_k(x_{kj}) - m_k(x_{kj})} \quad (21)$$

For “cost” type criteria,

$$Y_{kj} = \frac{\max(x_{kj}) - x_{kj}}{m_k(x_{kj}) - m_k(x_{kj})} \quad (22)$$

Using the above equations, the normalized expert weighted group decision matrix $Y = (Y_{kj})^T$ is obtained from the expert weighted group decision matrix.

(3) Determination of the positive ideal and negative ideal solution and Closeness Coefficients

Knowing the normalized expert weighted group decision matrix Y^k , the positive ideal and negative ideal solutions can be calculated as:

$$Y^+ = \{ \max_{1 \leq i \leq k} Y_{kj} \} = \{ Y_1^+, \dots, Y_n^+ \} \quad (23)$$

$$Y^- = \{ \min_{1 \leq i \leq k} Y_{kj} \} = \{ Y_1^-, \dots, Y_n^- \} \quad (24)$$

Then, the n-dimension Euclidean distances between each alternative subcontractor and the positive ideal solution and the negative ideal solution can be calculated while considering the weight of each criterion ω_j as:

$$Q_k^+ = \sqrt{\sum_{j=1}^n [(Y_{kj} - Y^+) \times \omega_j]^2} \quad (25)$$

$$Q_k^- = \sqrt{\sum_{j=1}^n [(Y_{kj} - Y^-) \times \omega_j]^2} \quad (26)$$

The closeness coefficient of each alternative subcontractor can be calculated as.

$$Z_k = \frac{Q_k^-}{Q_k^+ + Q_k^-}, (k = 1, \dots, g) \quad (27)$$

The subcontractors are then ranked based on their closeness coefficients and the subcontractor with the largest closeness coefficient is selected.

5. Numerical Example

In this example, a general contractor subcontracted the curtain wall project of a large factory building and asked four experts, $E_i = \{E_1, E_2, E_3, E_4\}$ to select the most appropriate subcontractor from four potential subcontractors, $S_k = \{S_1, S_2, S_3, S_4\}$. The evaluation criteria set is $U_j = \{U_1, \dots, U_{10}\}$. The criteria in the criteria set are evaluated using both qualitative and quantitative criteria. “Price”, “Experience Modification Ratio”, “Amount of Subcontracts”, “Cost overrun”, “Schedule overrun” are evaluated using quantitative measures that include both precise numbers and numerical ranges, whereas “Quality of work”, “Experience With Similar Projects”, “Past relationship with general contractor”, “Technical competence”, “Management competence” are evaluated by experts using a five-level fuzzy qualitative linguistic system, as shown in Table 1.

The decision matrices for the four construction subcontractors, $S_k = \{S_1, S_2, S_3, S_4\}$, are shown below. These matrices contain different types of data (i.e., precise numbers, numerical ranges, and linguistic terms).

$$A^1 = \begin{bmatrix} & U_1 & U_2 & U_3 & U_4 & U_5 & U_6 & U_7 & U_8 & U_9 & U_{10} \\ E_1 & 1.3 & 1.1 & 30\% & [1, 1.2] & [0.9, 1.1] & M & H & VH & VH & VH \\ E_2 & 1.3 & 1.1 & 30\% & [1, 1.2] & [0.9, 1.1] & M & M & VH & VH & H \\ E_3 & 1.3 & 1.1 & 30\% & [1, 1.2] & [0.9, 1.1] & H & H & H & VH & H \\ E_4 & 1.3 & 1.1 & 30\% & [1, 1.2] & [0.9, 1.1] & H & H & VH & VH & VH \end{bmatrix}$$

$$A^2 = \begin{bmatrix} & U_1 & U_2 & U_3 & U_4 & U_5 & U_6 & U_7 & U_8 & U_9 & U_{10} \\ E_1 & 1.15 & 0.9 & 25\% & [1, 1.4] & [0.95, 1.05] & VH & M & M & H & M \\ E_2 & 1.15 & 0.9 & 25\% & [1, 1.4] & [0.95, 1.05] & H & H & H & H & L \\ E_3 & 1.15 & 0.9 & 25\% & [1, 1.4] & [0.95, 1.05] & VH & M & H & M & H \\ E_4 & 1.15 & 0.9 & 25\% & [1, 1.4] & [0.95, 1.05] & VH & L & M & VH & L \end{bmatrix}$$

$$A^3 = \begin{bmatrix} & U_1 & U_2 & U_3 & U_4 & U_5 & U_6 & U_7 & U_8 & U_9 & U_{10} \\ E_1 & 1.35 & 0.9 & 40\% & [1, 1.3] & [1, 1.15] & H & H & H & VH & M \\ E_2 & 1.35 & 0.9 & 40\% & [1, 1.3] & [1, 1.15] & VH & H & VH & VH & M \\ E_3 & 1.35 & 0.9 & 40\% & [1, 1.3] & [1, 1.15] & M & VH & H & H & M \\ E_4 & 1.35 & 0.9 & 40\% & [1, 1.3] & [1, 1.15] & H & H & H & VH & M \end{bmatrix}$$

$$A^4 = \begin{bmatrix} & U_1 & U_2 & U_3 & U_4 & U_5 & U_6 & U_7 & U_8 & U_9 & U_{10} \\ E_1 & 1.25 & 0.7 & 20\% & [1.05, 1.15] & [0.9, 1.25] & L & VH & H & H & H \\ E_2 & 1.25 & 0.7 & 20\% & [1.05, 1.15] & [0.9, 1.25] & L & VH & M & VH & H \\ E_3 & 1.25 & 0.7 & 20\% & [1.05, 1.15] & [0.9, 1.25] & M & VH & H & M & H \\ E_4 & 1.25 & 0.7 & 20\% & [1.05, 1.15] & [0.9, 1.25] & L & VH & H & H & VH \end{bmatrix}$$

The following steps are used to complete the selection process:

(1) Conversion of data to precise numbers

After using Equation (4) to convert numerical ranges to precise numbers and using Table 1 and Equation (5) to convert fuzzy linguistic terms to precise numbers, the converted decision matrices for construction subcontractor S_k are $R^k = (r_{ij}^k)^T$:

$$R^1 = \begin{bmatrix} & U_1 & U_2 & U_3 & U_4 & U_5 & U_6 & U_7 & U_8 & U_9 & U_{10} \\ E_1 & 1.3 & 1.1 & 30\% & 1.067 & 0.967 & 0.5 & 0.786 & 0.964 & 0.964 & 0.964 \\ E_2 & 1.3 & 1.1 & 30\% & 1.067 & 0.967 & 0.5 & 0.5 & 0.964 & 0.964 & 0.786 \\ E_3 & 1.3 & 1.1 & 30\% & 1.067 & 0.967 & 0.786 & 0.786 & 0.786 & 0.964 & 0.786 \\ E_4 & 1.3 & 1.1 & 30\% & 1.067 & 0.967 & 0.786 & 0.786 & 0.964 & 0.964 & 0.964 \end{bmatrix}$$

$$R^2 = \begin{bmatrix} & U_1 & U_2 & U_3 & U_4 & U_5 & U_6 & U_7 & U_8 & U_9 & U_{10} \\ E_1 & 1.15 & 0.9 & 25\% & 1.133 & 0.983 & 0.964 & 0.5 & 0.5 & 0.786 & 0.5 \\ E_2 & 1.15 & 0.9 & 25\% & 1.133 & 0.983 & 0.786 & 0.786 & 0.786 & 0.786 & 0.214 \\ E_3 & 1.15 & 0.9 & 25\% & 1.133 & 0.983 & 0.964 & 0.5 & 0.786 & 0.5 & 0.786 \\ E_4 & 1.15 & 0.9 & 25\% & 1.133 & 0.983 & 0.964 & 0.214 & 0.5 & 0.964 & 0.214 \end{bmatrix}$$

$$R^3 = \begin{bmatrix} & U_1 & U_2 & U_3 & U_4 & U_5 & U_6 & U_7 & U_8 & U_9 & U_{10} \\ E_1 & 1.35 & 0.9 & 40\% & 1.1 & 1.05 & 0.786 & 0.786 & 0.786 & 0.964 & 0.5 \\ E_2 & 1.35 & 0.9 & 40\% & 1.1 & 1.05 & 0.964 & 0.786 & 0.964 & 0.964 & 0.5 \\ E_3 & 1.35 & 0.9 & 40\% & 1.1 & 1.05 & 0.5 & 0.964 & 0.786 & 0.786 & 0.5 \\ E_4 & 1.35 & 0.9 & 40\% & 1.1 & 1.05 & 0.786 & 0.786 & 0.786 & 0.964 & 0.5 \end{bmatrix}$$

$$R^4 = \begin{bmatrix} & U_1 & U_2 & U_3 & U_4 & U_5 & U_6 & U_7 & U_8 & U_9 & U_{10} \\ E_1 & 1.25 & 0.7 & 20\% & 1.083 & 1.017 & 0.214 & 0.964 & 0.786 & 0.786 & 0.786 \\ E_2 & 1.25 & 0.7 & 20\% & 1.083 & 1.017 & 0.214 & 0.964 & 0.5 & 0.964 & 0.786 \\ E_3 & 1.25 & 0.7 & 20\% & 1.083 & 1.017 & 0.5 & 0.964 & 0.786 & 0.5 & 0.786 \\ E_4 & 1.25 & 0.7 & 20\% & 1.083 & 1.017 & 0.214 & 0.964 & 0.786 & 0.786 & 0.964 \end{bmatrix}$$

(2) Determination of Evaluation Criteria's Weights using SEWM

The four experts ranked the importance of the criteria set $U_j = \{U_1, \dots, U_{10}\}$ based on their experience and Table 2 and the initial criteria importance matrix was obtained as:

$$B_{4 \times 10} = \begin{bmatrix} & U_1 & U_2 & U_3 & U_4 & U_5 & U_6 & U_7 & U_8 & U_9 & U_{10} \\ E_1 & 1 & 3 & 4 & 2 & 1 & 2 & 3 & 2 & 3 & 4 \\ E_2 & 1 & 2 & 2 & 3 & 1 & 4 & 2 & 3 & 3 & 5 \\ E_3 & 2 & 2 & 4 & 1 & 2 & 2 & 3 & 2 & 4 & 5 \\ E_4 & 1 & 1 & 5 & 3 & 2 & 4 & 3 & 2 & 3 & 4 \end{bmatrix}$$

To reduce the “data noise” associated with the initial criteria importance matrix, the initial criteria Importance matrix is transformed to an adjusted criteria importance matrix $C_{ij} = (\mu_{ij})^T$ using SWEM and the membership function provided in Equation (7), where $\varepsilon = n + 2 = 12$ and $\mu_{ij} = \frac{\ln(12 - B_{ij})}{\ln(12 - 1)}$.

Then, using Equations (8)–(12), the criteria weight vector W is determined as:

$$W = (0.108, 0.0103, 0.093, 0.101, 0.105, 0.098, 0.099, 0.103, 0.098, 0.090)^T; \lambda = (0.300, 0.214, 0.250, 0.236)^T$$

(3) Determination of Experts' Weights Using the Method of Minimum Deviation

Using the initial criteria importance matrix and Equations (13)–(15), the expert weight assignment model can be constructed. Then, using Equations (16)–(18), the vector of experts' weights, λ , can be determined as:

$$\lambda = (0.300, 0.214, 0.250, 0.236)^T$$

(4) Subcontractor Selection using TOPSIS

The expert weighted group decision matrix X is calculated by combining the subcontractor decision matrices $R^k = (r_{ij}^k)^T$ for all of the S_k evaluated subcontractors and the vector of experts' weights $\lambda = (\lambda_1, \dots, \lambda_n)^T$ using Equation (19) as:

$$X = \begin{bmatrix} & U_1 & U_2 & U_3 & U_4 & U_5 & U_6 & U_7 & U_8 & U_9 & U_{10} \\ S_1 & 1.3 & 1.1 & 30\% & 1.067 & 0.967 & 0.639 & 0.725 & 0.92 & 0.964 & 0.881 \\ S_2 & 1.15 & 0.9 & 25\% & 1.133 & 0.983 & 0.926 & 0.494 & 0.633 & 0.757 & 0.443 \\ S_3 & 1.35 & 0.9 & 40\% & 1.1 & 1.05 & 0.753 & 0.831 & 0.824 & 0.92 & 0.5 \\ S_4 & 1.25 & 0.7 & 20\% & 1.083 & 1.017 & 0.286 & 0.964 & 0.725 & 0.753 & 0.828 \end{bmatrix}$$

Using Equations (21) and (22), the normalized expert weighted group decision matrix $Y = (Y_{kj})^T$ is obtained from the expert weighted group decision matrix X as:

$$Y = \begin{bmatrix} & U_1 & U_2 & U_3 & U_4 & U_5 & U_6 & U_7 & U_8 & U_9 & U_{10} \\ S_1 & 0.25 & 0 & 0.5 & 1 & 1 & 0.552 & 0.491 & 1 & 1 & 1 \\ S_2 & 1 & 0.5 & 0.75 & 0 & 0.807 & 1 & 0 & 0 & 0.017 & 0 \\ S_3 & 0 & 0.5 & 0 & 0.5 & 0 & 0.729 & 0.716 & 0.666 & 0.789 & 0.13 \\ S_4 & 0.5 & 1 & 1 & 0.758 & 0.398 & 0 & 1 & 0.32 & 0 & 0.879 \end{bmatrix}$$

The Euclidean distances between each subcontractor alternative and the positive ideal solution and the negative ideal solution, and the closeness coefficient, are calculated as:

$$Z_1 = \frac{Q_1^-}{Q_1^+ + Q_1^-} = \frac{0.241}{0.154 + 0.241} = 0.609, Z_2 = \frac{0.190}{0.228 + 0.190} = 0.455, \\ Z_3 = \frac{0.162}{0.214 + 0.162} = 0.431, Z_4 = \frac{0.217}{0.179 + 0.217} = 0.548$$

The subcontractors are then ranked based on their closeness coefficients $Z_1 > Z_4 > Z_2 > Z_3$ and subcontractor S_1 , with the largest closeness coefficient, is recommended for selection.

6. Discussion

Although several subcontractor selection models were developed in the past, they attempted to provide a “one-size-fits-all” solution and, as such, were not widely utilized by construction companies who significantly vary in size, type of work, and project delivery system used. In this paper, the authors made the case for developing different subcontractor selection models for different situations and project conditions. The paper then presented a subcontractor selection model that was developed to consider the specific needs of large construction companies. Such large construction companies collect massive amount of different types of data and information documenting subcontractors’ performance which, if analyzed properly, can improve the subcontractor selection process. Furthermore, large construction companies employ a large number of project managers who have experience working with an even larger number of subcontractors. Such experiences can offer a significant competitive advantage to the company if captured effectively in the company’s system and used when selecting subcontractors for future projects. It is important to note that when considering the potential of big data for improving decision making in large construction companies, it is not the amount of data that is important but rather what companies do with all of these data that matters. It is, therefore, important to develop models that can effectively use the data, such as the proposed model.

This study added to the body of knowledge by developing a hybrid model that integrates the structure entropy weight (SEW) and the technique for order preference by similarity to an ideal solution (TOPSIS) methods. The hybrid model uses the structure entropy weight method to calculate the weights of the selection criteria based on experts’ judgments while offsetting the uncertainties associated with their judgements. The method of minimum deviation is then used to determine the weights of experts’ opinions to account for their varying level of expertise and knowledge. Finally, TOPSIS is used to rank and select the most suitable construction subcontractor.

7. Conclusions

In this paper, a hybrid TOPSIS-SEW group subcontractor selection model was proposed for use by large construction companies. The proposed system had several advantages including: (1) it can be easily implemented using a spreadsheet allowing the selection process to be completed in a timely manner as dictated by the competitive nature of the construction industry; (2) it is capable of utilizing the large amount of subcontractors’ performance data collected by some construction companies in different data formats (e.g., precise numbers, numerical ranges, and linguistic terms); (3) it is capable of handling a large number of criteria and calculating the weights to the various criteria in a speedy

manner; and (4) it can integrate experts' judgments while accounting for their varying level of expertise and correcting for their biases.

The case study included in this paper illustrated that the proposed model was clear and concise, and can be easily adapted by large construction companies who prefer to utilize selection criteria that may be different than those used in the case study and which may include sustainable construction experience [45] and/or use of construction robots [46]. While this study was applied to construction subcontractors' selection, the proposed methodology can be easily extended to various decision-making scenarios with similar requirements.

It should be noted that in the proposed methodology, both the criteria's weights and experts' weights were determined based on input provided as "precise" numbers. It is recommended that the model be extended in future research to handle situations where input used to determine criteria and experts' weight is provided as "fuzzy" data.

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