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AN INTEGRATION METHOD FOR SUPPLIER SELECTION: A PRACTICAL STUDY IN THE INDONESIAN CONCRETE COMPANY

AGUS RISTONO*

Department of Industrial Engineering, University of Pembangunan Nasional Veteran Yogyakarta, Yogyakarta, Indonesia

**Corresponding author: agus.ristono@upnyk.ac.id*

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ABSTRACT: The construction of toll roads in Indonesia has massively increased the need for concrete. Therefore, concrete manufacturing companies must select new raw material suppliers for concrete. This selection is based on several criteria, including qualitative and quantitative criteria. This study proposes a new methodology for supplier selection. The model captures decision-makers' dynamics in ranking suppliers by integrating quantitative and qualitative criteria. The first stage in the proposed model is determining the criteria using the Fuzzy Delphi Method (FDM). The second stage is weighting the criteria using the Fuzzy Step-wise Assessment Ratio (F-SWARA) II and the Method Based on Removal Effects of Criteria (MEREC). The last stage is supplier assessment using Fuzzy Measurement of Alternatives and Ranking According to Compromise Solution (F-MARCOS). One of Indonesia's largest concrete manufacturing companies was used to validate the proposed model. The results showed that the proposed model is valid and more effective than some previous methods. The company in the case study experienced a 5% reduction in production costs in the later stages of the toll project, following several months of implementation, indicating the effectiveness of the proposed methodology.

ABSTRAK: Pembinaan jalan tol di Indonesia telah meningkatkan keperluan konkrit secara besar-besaran. Oleh itu, syarikat pembuatan konkrit mesti memilih pembekal bahan mentah baru konkrit. Pemilihan ini berdasarkan beberapa kriteria, termasuk kriteria kualitatif dan kuantitatif. Kajian ini mencadangkan metodologi baru untuk pemilihan pembekal. Model ini menfokuskan pembuat keputusan dinamik dalam kedudukan pembekal dengan menyepadu kedua-dua kriteria kuantitatif dan kualitatif. Peringkat pertama dalam model yang dicadangkan ini adalah menentukan kriteria menggunakan Kaedah Rawak Delphi (FDM). Peringkat kedua adalah menimbang kriteria menggunakan Nisbah Pentaksiran Rawak Langkah-Bijak (F-SWARA) II dan kaedah berdasarkan Kriteria Kesan Pengasingan (MEREC). Peringkat terakhir merupakan penilaian pembekal menggunakan Solusi Kompromi berdasarkan Pengukuran Rawak Alternatif dan Kedudukan (F-MARCOS). Salah satu syarikat pembuatan konkrit terbesar di Indonesia telah digunakan bagi mengesahkan model yang dicadangkan. Dapatan kajian menunjukkan bahawa model yang dicadangkan ini adalah sah dan lebih berkesan berbanding beberapa kaedah sebelumnya. Syarikat dalam kes kajian mengalami pengurangan 5% dalam kos pengeluaran pada peringkat akhir projek tol, iaitu selepas beberapa bulan pelaksanaan, menunjukkan keberkesanan metodologi yang dicadangkan.

KEYWORDS: *Fuzzy Delphi Method, F-SWARA II, MEREC, F-MARCOS, Supplier selection*

1. INTRODUCTION

The Ministry of Public Works (PU) Indonesia plans to construct freeways or toll roads along 17,865.43 kilometers (km) between 2025 and 2040. Meanwhile, Java is the island most connected to toll roads, with an operating toll road length of 1,632.63 km. However, this length is still far from the total planned toll road length, which is 4,688.94 km. Due to this policy implemented by the Indonesian government, concrete will be required. PT Wika Beton, one of Indonesia's leading concrete manufacturers, will enhance its production capacity to prepare for the anticipated rise in demand for concrete. As a result, acquiring materials from additional raw material providers is essential.

PT Wika Beton selects its suppliers not for the short term but to establish long-term partners. This is mainly because raw materials are an essential component and play a crucial role in the development of our organization. In the long term, suppliers are required to ensure the availability of essential materials. Consequently, it is imperative to identify the appropriate supplier. Suppliers are indispensable to the organization's supply chain. Supply chain management significantly influences enterprise performance and profitability. Consequently, it is imperative to cultivate positive relationships with suppliers and preserve a robust supply chain.

Supplier selection can be done using Multi-Criteria Decision Making (MCDM). There are manyCDM, such as Analytical Hierarchy Process (AHP), Analytic Network Process (ANP), Preference Ranking Organization Method for Enrichment Evaluations (PROMETHEE), VIšekriterijumska Optimizacija I Kompromisno Rešenje (VIKOR), Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), Elimination et Choix Traduisant la Réalité/Elimination and Choice Expressing Reality (ELECTRE), Multi-Objective Optimization based on Ratio Analysis (MOORA), Complex Proportional Assessment (COPRAS), and the Measurement of Alternatives and Ranking according to the Compromise Solution (MARCOS). Recent studies show the latest developments in supplier selection methods, including four strategies [1]. They are (1) utilizing fuzzy logic, which is suitable for the dynamic and data-rich environment of Industry 4.0; (2) using mixed MCDM strategies to handle the complex problems of supplier selection in Industry 4.0; (3) using hybrid fuzzy MCDM techniques, which offer a more thorough and complex decision-making process [1].

The MARCOS method demonstrates high stability in ranking options than others [2]. It can identify the optimal solution regardless of the number of alternatives or the weighting method employed [3]. The criteria in MARCOS consist of qualitative and quantitative criteria, so both need to be weighted. Qualitative criteria can only be assessed using the decision maker's perception, while quantitative criteria can be evaluated based on historical supplier data. The primary limitation of subjective weighting is its ineffectiveness as the number of criteria increases, including additional criteria, which can lead to decreased accuracy in these preferences [4]. The combined weighting approach reduces the potential bias associated with a singular subjective or objective weight [4].

Throughout its evolution, MARCOS has found extensive utility in addressing issues related to supplier selection. Badi and Pamucar [5] used the MARCOS system to choose the best supplier and the Grey theory to establish the criteria weights in steel companies. Chattopadhyay et al. [6] proposed the D number theory to incorporate MARCOS into the supplier selection process in the iron and steel sector. Taş et al. [7] employed F-MARCOS and Spherical Fuzzy Stepwise Weight Assessment Ratio Analysis (SF-SWARA) to identify environmentally conscious vendors for textile businesses. To help textile businesses choose ecologically friendly vendors, Tus and Aytac-Adali [8] presented a strategy that merges F-

SWARA and F-MARCOS. Abdulla et al. (2023) suggested integrating MARCOS with machine learning for supplier selection. Y. Wang et al. [9] present two methods for selecting sustainable food suppliers: PF-CRITIC, which uses Pythagorean fuzzy measurement of alternatives and ranking to compromise, and PF-MARCOS, which uses weights to determine the criterion. The position of the proposed method in supplier selection research utilizing MARCOS is illustrated in Table 1.

Table 1. Supplier selection research using MARCOS

Ref	Criteria selection	Criteria weighting		Alternative selection		Case
		Objective method	Subjective method	Original MARCOS	Extended MARCOS	
[5]	-	-	Grey method	MARCOS	-	Steel-making company
[6]	-	-	-	-	D-MARCOS	Steel and iron industry
[7]	-	-	SF-SWARA	-	Fuzzy MARCOS	Green suppliers in textile companies
[8]	-	-	F-SWARA	-	Fuzzy MARCOS	Green suppliers in textile companies
[10]	-	-	-	MARCOS	-	General
[11]	-	-	Machine learning	MARCOS	-	Oil and gas sector
[9]	-	PF-CRITIC	-	-	PF-MARCOS	Sustainable food suppliers
Proposed method	Fuzzy Delphi	MEREC	F-SWARA II	-	Fuzzy MARCOS	Concrete manufacturing company

Previous research on supplier selection utilizing MARCOS only partially used subjective or objective weighting. Such as Badi and Pamucar [5], Taş et al. [7], Tus and Aytac-Adali [8], and Abdulla et al. [11] used only subjective criteria for weighting. Whereas Y. Wang et al. [9] used only objective weighting. However, not all criteria can be weighed objectively or subjectively. It depends on its characteristics. So, it is prone to bias [4]. In addition, the criteria in previous studies already exist. The process of determining these criteria is essential in selecting suppliers [4], The proposed method then employs Fuzzy Delphi for criteria selection and integrates objective and subjective criteria weighting.

2. METHODS

The proposed method has three stages. The first stage is determining the supplier selection criteria using FDM. The second stage is weighting criteria using F SWARA II and MEREC. The last stage is supplier assessment. Some potential criteria are selected using FDM to produce the chosen criteria. The chosen criteria consist of qualitative criteria and quantitative criteria. Qualitative criteria are weighted using F SWARA II, while quantitative criteria are weighted using MEREC. Supplier performance assessment using F MARCOS based on weighted criteria. The criteria are based on the weighting of F SWARA II and MEREC.

The selection of criteria uses FDM because FDM can reduce subjectivity in decision-making based on expert opinion, produce more objective agreement in the early stages of research or selection of essential factors, and does not require many iterations compared to classical Delphi [12]. The objective criteria weighting uses MEREC because MEREC is a more efficient, precise, and accurate objective weighting than other methods [3]. The MEREC is recommended for application because of its high accuracy [3]. The subjective criteria weighting uses SWARA because SWARA is more straightforward than other subjective methods, and experts can participate more spontaneously [13]. Supplier assessment uses MARCOS because it is more stable than other MCDM [2] and can always find the best one, no matter how many options are considered or how the weights are distributed [3].

2.1. Fuzzy Delphi Method

Compared to other expert-based methods (such as AHP or fuzzy AHP), the FDM can obtain expert consensus to determine essential factors or variables in a study [14]. AHP or fuzzy AHP can only choose the priority weight between criteria and alternatives in the multi-criteria decision-making process [1]. The FDM's steps are:

- **Step 1**: Expert panel. This document includes the division head and all procurement, building, and commissioning staff members. They have been employed by comparable organizations for over 15 years, which is why their responses are credible. Ten specialists satisfy these procurement, building, and commissioning prerequisites. This investigation exclusively employed the cases of PT. Wika Beton. All of the specialists selected are experts in supplier selection at PT. Wika Beton, which is why they are the population used in FDM.
- **Step 2**: List of the potential criteria. The most widely used criteria in the literature are price, reject, delivery [6], and service [8]. Price and reject are critical criteria because they directly affect the company's profit. The delivery and service criteria affect production lead time and its impact on increasing penalty costs. This will reduce the company's profit. In the FGD with decision makers at the largest concrete company in Indonesia, additional criteria were obtained: communication and flexibility. These two criteria have an impact on company trust. The selection of suppliers in concrete manufacturing is not only temporary but also for the long term.
- **Step 3**: The experts measure each criterion using linguistic variables (LV). The $\mu_{\tilde{n}}$ ranges from 1 to 0 in the LV, from Very Suitable to Very Unsuitable, as seen in Table 2. A score is represented as a TFN $\tilde{n}_i^k = (n_{1i}^k, n_{2i}^k, n_{3i}^k)$ [14].
- **Step 4.a**: Determining threshold value (Th_i) using Eq. (1) [14]. The minimum threshold on each criterion i is 0.2 [15].

$$Th_i = \left(\frac{1}{K}\right)\sum_{k=1}^{K}\sqrt{\frac{1}{3}\left[(n_{i1}^k - a_{i1})^2 + (n_{i2}^k - a_{i2})^2 + (n_{i3}^k - a_{i3})^2\right]} \tag{1}$$

- **Step 4.b**: Testing the experts' consensus using Eq. (2) [14]. The minimum level of experts' consensus is 75% for every criterion [15].

$$EA_i = \left\{\frac{\sum_{k=0}^{K}\left(c_i^k\right)\begin{cases} c_i^k=1, if\ d \le 0.2 \\ 0, \quad otherwise\end{cases}}{K}\right\} \times 100\% \tag{2}$$

- **Step 4.c**: Defuzzification. The aggregate TFN is calculated using Eqs. (3) [14]. Then the calculation of the α-cut using Eq. (4) [14] which this value must be more than 0.5 [15].

$$\tilde{n}_i = \left(\min\left(n_{i1}^k\right), \left[\prod_{k=1}^{K} n_{i2}^k\right]^{\frac{1}{K}}, \max\left(n_{i3}^k\right)\right) \tag{3}$$

$$\alpha_{cut} = n_{i1} + \frac{(n_{i3}-n_{i1})+(n_{i2}-n_{i1})}{3} \tag{4}$$

The diagram of the FDM can be seen in Figure 1. After forming the expert panel, the second step is collecting data from experts. The questionnaire is given to the expert panel. The answers are converted to fuzzy numbers. After that, the fuzzy average calculation is carried out. The third step is defuzzification (conversion to crisp value) to obtain a precise value. The fourth step is determining the Expert consensus, namely, the minimum threshold on each criterion i is 0.2; the minimum level of experts' consensus is 75% for each criterion; and the α-cut value must be more than 0.5. If the factors do not reach consensus, reiterate with a revised questionnaire. Final Decision Factors that reach consensus are included in the analysis. After iteration, factors that still do not meet consensus can be removed or reviewed.

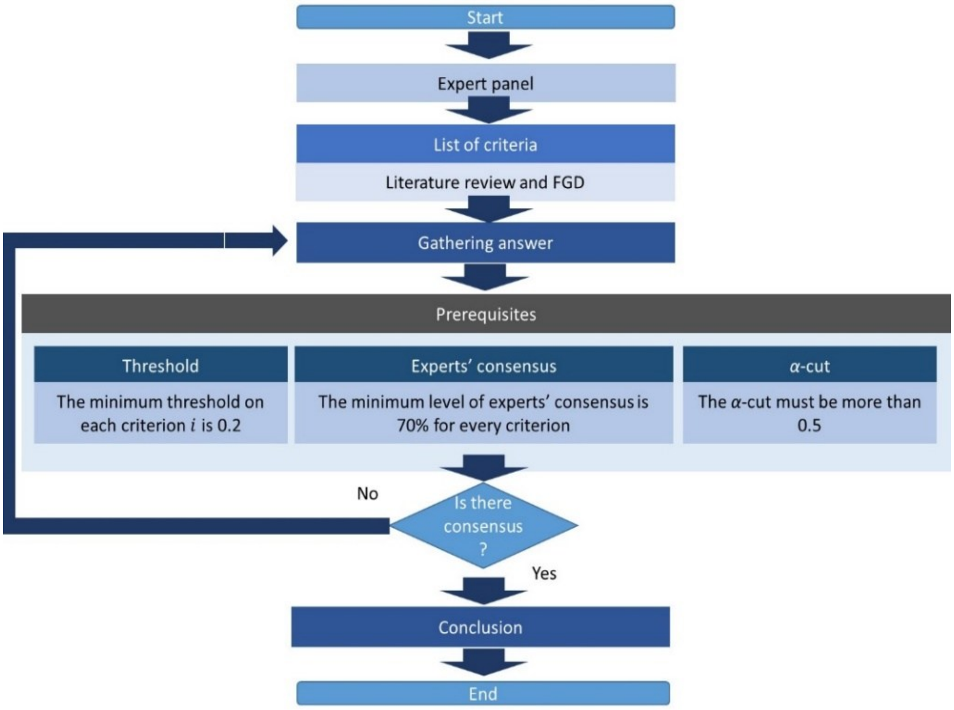

Figure 1. Flow chart of the FDM [12].

Table 2. Scale of fuzzy numbers in the FDM

No	5-Point LV	Most reasonable (n_2)	Pessimistic value (n_1)	Optimistic value (n_3)
1	Very Suitable	0.9	0.8	1
2	Suitable	0.7	0.6	0.8
3	Acceptable	0.5	0.4	0.6
4	Unsuitable	0.3	0.2	0.4
5	Very Unsuitable	0.1	0	0.2

2.2. Fuzzy SWARA II

SWARA II is an improved version of SWARA, as presented by Keshavarz-Ghorabaee [16]. However, specific adjustments to the methodology make SWARA II more attainable and practical for decision-makers. This study proposed integrating fuzzy theory with the SWARA II to enhance its intrinsic ambiguity and account for data imprecision and uncertainty. The steps of the Fuzzy SWARA II are as follows and can be seen in Figure 2.

- **Step 1**: Determination of the rank of the j^{th} criterion using the symbol t_j ($t_j \epsilon\{1, 2, 3, \dots, n\}$).
- **Step 2**: Ask the decision-maker to specify each criterion's relative preference ($\widetilde{RP}$) by comparing it ($[t_j]^{th}$) with the following criterion ($[t_j+1]^{th}$) in the prioritized list from Step 1. This study employs linguistic variables (LVs) and associated values, as illustrated in Table 3.
- **Step 3**: Determine each criterion's fuzzy number of the preference degree ($\widetilde{PD}$) using Eq. (5).

$$\widetilde{PD}_{[t_j]} = u\left[\tilde{P}_{[t_j]}\right] = \left[\frac{\tilde{P}_{[t_j]}}{10}\right]^2 \tag{5}$$

- **Step 4**: Calculate the fuzzy number of the relative weighting coefficients using Eq. (6). The coefficients are established based on the arrangement of each criterion within the ordered list and the corresponding fuzzy number values of $\widetilde{PD}$. Starting from the nth criterion, the following equation is utilized for calculation.

$$\tilde{V}_{[t_j-1]} = \left(1 + \widetilde{PD}_{[t_j-1]}\right) . \tilde{V}_{[t_j]} \tag{6}$$

- **Step 5**: The relative weights of the evaluation criteria are determined using Eq. (7).

$$\widetilde{W}_j^s = \frac{\tilde{V}_{[t_j]}}{\tilde{V}_{[t_1]} \oplus \tilde{V}_{[t_2]} \oplus \dots \tilde{V}_{[t_n]}} \tag{7}$$

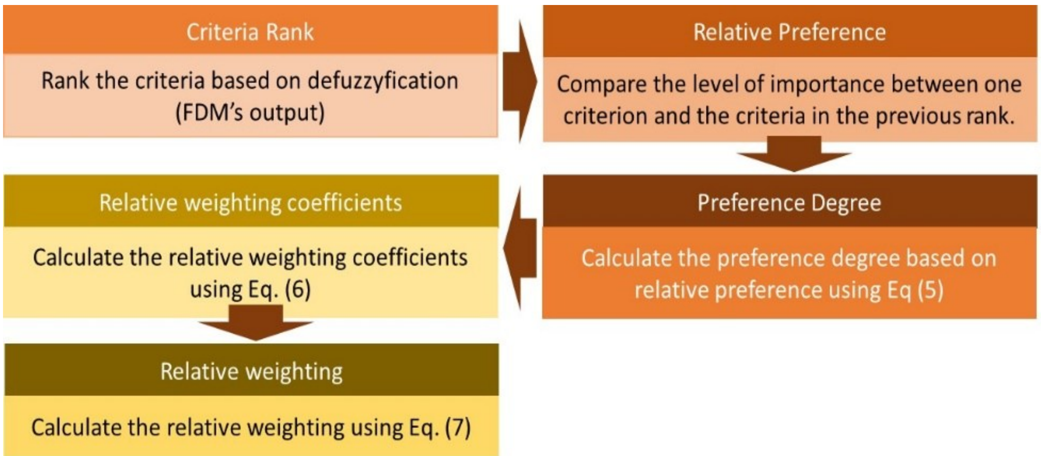

Figure 2. Step of the F SWARA II.

2.3. MEREC

The MEREC stages in the proposed method can be seen in Çelebi Demirarslan et al. [17]. The MEREC calculates weights based on the contribution of each criterion to the total difference between alternatives [17]. In contrast, the CRITIC is based on the correlation between criteria [18], and Entropy is based on the probability distribution of data in the criteria [19]. Therefore, the CRITIC is ineffective if there is no correlation between the criteria [18], and conversely, Entropy is useless if there is a correlation between criteria [19]. However, the MEREC is unaffected by the presence or absence of correlation between criteria [17]. The MEREC is not very sensitive to data scale because it is based on variation between criteria [17]. At the same time, the CRITIC is less flexible for data with different scales, especially if the data is not normalized first [18]. The entropy is sensitive to un-normalized data, requiring more careful preprocessing [19]. Although the Entropy is easy to implement and calculate, it is less accurate if the data has a uniform distribution pattern, because the weights can become insignificant [19]. At the same time, the MEREC is not affected by such patterns.

2.4. Fuzzy MARCOS

The proposed method's F-MARCOS stages can be seen in Stanković et al. [20]. Table 3 illustrates the transformation of the linguistic variable into a fuzzy initial decision matrix.

Table 3. Scale of fuzzy numbers

No	9-Point LV in the F MARCOS [20]	Relative Preference (n_1, n_2, n_3)	9-Point LV in the F SWARA II	Relative Preference (n_1, n_2, n_3)
1	Extremely poor (EP)	(1, 1, 1)	Very very low (VVL)	(1, 1, 2)
2	Very poor (VP)	(1, 1, 3)	Very low (VL)	(1, 2, 3)
3	Poor (P)	(1, 3, 3)	Low (L)	(2, 3, 4)
4	Medium poor (MP)	(3, 3, 5)	Medium-low (ML)	(3, 4, 5)
5	Medium (M)	(3, 5, 5)	Medium (M)	(4, 5, 6)
6	Medium good (MG)	(5, 5, 7)	Medium-high (MH)	(5, 6, 7)
7	Good (G)	(5, 7, 7)	High (H)	(6, 7, 8)
8	Excellent (VG)	(7, 7, 9)	Very high (VH)	(7, 8, 9)
9	Extremely good (EG)	(7, 9, 9)	Very very high (VVH)	(8, 9, 9)

Table 4. Linguistic variable of the criteria assessment

		Criteria						
		C_1	C_2	C_3	C_4	C_5	C_6	C_7
1	D_1	Very Suitable	Very Suitable	Very Suitable	Very Suitable	Acceptable	Suitable	Suitable
2	D_2	Very Suitable	Very Suitable	Suitable	Suitable	Suitable	Very Suitable	Acceptable
3	D_3	Suitable	Very Suitable	Very Suitable	Very Suitable	Very Suitable	Suitable	Suitable
4	D_4	Very Suitable	Suitable	Suitable	Suitable	Suitable	Acceptable	Very Suitable
5	D_5	Very Suitable	Suitable	Very Suitable	Very Suitable	Acceptable	Suitable	Suitable
6	D_6	Suitable	Very Suitable	Suitable	Acceptable	Suitable	Very Suitable	Very Suitable
7	D_7	Very Suitable	Suitable	Very Suitable	Very Suitable	Acceptable	Suitable	Suitable
8	D_8	Very Suitable	Suitable	Suitable	Suitable	Acceptable	Very Suitable	Suitable
9	D_9	Very Suitable	Very Suitable	Acceptable	Very Suitable	Acceptable	Suitable	Very Suitable
10	D_{10}	Very Suitable	Very Suitable	Acceptable	Suitable	Very Suitable	Suitable	Very Suitable

Table 5. Fuzzy number of the criteria assessment linguistic variable

		Criteria						
		C_1	C_2	C_3	C_4	C_5	C_6	C_7
1	D_1	Very Suitable	Very Suitable	Very Suitable	Very Suitable	Acceptable	Suitable	Suitable
2	D_2	Very Suitable	Very Suitable	Suitable	Suitable	Suitable	Very Suitable	Acceptable
3	D_3	Suitable	Very Suitable	Very Suitable	Very Suitable	Very Suitable	Suitable	Suitable
4	D_4	Very Suitable	Suitable	Suitable	Suitable	Suitable	Acceptable	Very Suitable
5	D_5	Very Suitable	Suitable	Very Suitable	Very Suitable	Acceptable	Suitable	Suitable
6	D_6	Suitable	Very Suitable	Suitable	Acceptable	Suitable	Very Suitable	Very Suitable
7	D_7	Very Suitable	Suitable	Very Suitable	Very Suitable	Acceptable	Suitable	Suitable
8	D_8	Very Suitable	Suitable	Suitable	Suitable	Acceptable	Very Suitable	Suitable
9	D_9	Very Suitable	Very Suitable	Acceptable	Very Suitable	Acceptable	Suitable	Very Suitable
10	D_{10}	Very Suitable	Very Suitable	Acceptable	Suitable	Very Suitable	Suitable	Very Suitable

3. RESULTS

3.1. Criteria selection

Seven evaluation criteria were established to identify the optimal supplier for PT Wika Beton: reject (c_1), delivery (c_2), price (c_3), communication (c_4), complaint procedure (c_5), service (c_6), and flexibility (c_7). Table 4 presents the assessment criteria decision-makers utilize in their expert evaluations—step two. The experts' responses on the 5-point linguistic scale were converted into a fuzzy number consisting of three specific values: n_1, n_2, and n_3.

Table 6. The threshold

		Criteria						
		C_1	C_2	C_3	C_4	C_5	C_6	C_7
1	D_1	0.04	0.04	0.04	0.04	0.36	0.16	0.16
2	D_2	0.04	0.04	0.16	0.16	0.16	0.04	0.36
3	D_3	0.16	0.04	0.04	0.04	0.04	0.16	0.16
4	D_4	0.04	0.16	0.16	0.16	0.16	0.36	0.04
5	D_5	0.04	0.16	0.04	0.04	0.36	0.16	0.16
6	D_6	0.16	0.04	0.16	0.36	0.16	0.04	0.04
7	D_7	0.04	0.16	0.04	0.04	0.36	0.16	0.16
8	D_8	0.04	0.16	0.16	0.16	0.36	0.04	0.16
9	D_9	0.04	0.04	0.36	0.04	0.36	0.16	0.04
10	D_{10}	0.04	0.04	0.36	0.16	0.04	0.16	0.04
$\sum_{k=1}^{K} d(\tilde{n}_i^k, \tilde{a}_i)$		0.64	0.88	1.52	1.20	2.36	1.44	1.32
Th_i		0.06	0.09	0.15	0.12	0.24	0.14	0.13

Table 6 presents the results of this step. The criterion c_5 (Thc_5) has a threshold value over 0.2, and the expert agreement is under 70%, leading to its removal. It transforms the computed average fuzzy rating score for each criterion i into its corresponding crisp values [14] utilizing Eq. (4).

Table 7. The expert's agreement value

		Triangular Fuzzy Numbers		**Condition of Defuzzification Process**		
	Criteria	Threshold Value	Percentage of Experts' Agreement	Fuzzy Number (A)	Ranking	Experts Consensus
1	C_1	0.06	100%	0.819	1	Accepted
2	C_2	0.09	100%	0.805	2	Accepted
3	C_3	0.15	80%	0.708	6	Accepted
4	C_4	0.12	90%	0.722	3	Accepted
5	C_5	0.24	50%	0.674	7	Not Accepted
6	C_6	0.24	90%	0.710	5	Accepted
7	C_7	0.13	90%	0.716	4	Accepted

Table 8. The results of F SWARA II

No	Criteria	Fuzzy number	BnFP	$[t_j]$	$\widetilde{RP}$	$\tilde{P}_{[t_j]}$			$\widetilde{PD}_{[t_j]}$			$\tilde{V}_{[t_j]}$			$\widetilde{W}_j^s$
						n_1	n_2	n_3	n_1	n_2	n_3	n_1	n_2	n_3	
		n_{41} 0.400													0.31
1	c_4	n_{42} 0.767	0.722	1	ML	3.00	4.00	5.00	0.09	0.16	0.25	1.36	1.58	1.86	0.40
		n_{43} 1.000													0.52
		n_{61} 0.400													0.29
2	c_6	n_{62} 0.748	0.716	2	MH	5.00	6.00	7.00	0.25	0.36	0.49	1.25	1.36	1.49	0.35
		n_{63} 1.000													0.41
		n_{71} 0.400													0.23
3	c_7	n_{72} 0.730	0.710	3	VL	1.00	2.00	3.00	0.01	0.04	0.09	1.00	1.00	1.00	0.25
		n_{73} 1.000													0.28

3.2. Criteria weighting

Three subjective criteria exist: communication (c_4), service (c_6), and flexibility (c_7). Table 8 is obtained using the F-SWARA II steps. The fuzzy weights for the subjective criteria are c_4 = (0.33; 0.40; 0.33), c_6 = (0.33; 0.35; 0.33), and c_7 = (0.33; 0.25; 0.33). Three objective criteria exist: reject (c_1), delivery (c_2), price (c_3). In contrast to subjective data, objective data are clear and precise. The objective data includes minimum, average, and maximum values—the application of objective criteria weighting through MEREC. The initial phase of MEREC involves the creation of a decision matrix. The second and third steps involve normalizing the decision matrix and assessing the overall performance of suppliers. The fourth step consists of calculating by removing each criterion. The fifth step is calculating the outcome effect of removing the j^{th} criterion. The final step involves establishing the criteria's weights**.** The MEREC method, as described by Çelebi Demirarslan et al. [17], is employed to carry out these steps, resulting in Table 9. According to Table 10, the fuzzy weights for the objective criteria are c_1 = (0.290; 0.330; 0.340), c_2 = (0.230; 0.232; 0.349), and c_3 = (0.361; 0.428; 0.440).

Table 9. The results of MEREC

	Supplier	D_{ij}^{a}			N_{ij}^{a}			S_{ij}^{a}	$S_{ij}^{\prime a}$			E_{j}^{a}		
		C_1	C_2	C_3	C_1	C_2	C_3		C_1	C_2	C_3	C_1	C_2	C_3
1	PT.ISBS	0.07	4	60	0.714	0.750	0.667	0.295	0.208	0.221	0.189	0.087	0.074	0.106
2	PT.MS	0.05	3	50	1.000	1.000	0.800	0.072	0.072	0.072	0.000	0.000	0.000	0.072
3	PT.CBS	0.065	4	60	0.769	0.750	0.667	0.276	0.208	0.201	0.168	0.069	0.076	0.108
4	PT.JCT	0.06	3	40	0.833	1.000	1.000	0.059	0.000	0.059	0.059	0.059	0.000	0.000
	Weight(w_j^a)											0.330	0.230	0.440
	Supplier	D_{ij}^{b}			N_{ij}^{b}			S_{ij}^{b}	$S_{ij}^{\prime b}$			E_{j}^{b}		
		C_1	C_2	C_3	C_1	C_2	C_3		C_1	C_2	C_3	C_1	C_2	C_3
1	PT.ISBS	0.09	4.4	80	0.778	0.909	0.750	0.192	0.120	0.165	0.109	0.072	0.027	0.082
2	PT.MS	0.07	4.2	70	1.000	0.952	0.857	0.065	0.065	0.050	0.016	0.000	0.015	0.049
3	PT.CBS	0.085	5.2	80	0.824	0.769	0.750	0.222	0.168	0.149	0.142	0.053	0.073	0.080
4	PT.JCT	0.08	4	60	0.875	1.000	1.000	0.044	0.000	0.044	0.044	0.044	0.000	0.000
	Weight(w_j^b)											0.340	0.232	0.428
	Supplier	D_{ij}^{c}			N_{ij}^{c}			S_{ij}^{c}	$S_{ij}^{\prime c}$			E_{j}^{c}		
		C_1	C_2	C_3	C_1	C_2	C_3		C_1	C_2	C_3	C_1	C_2	C_3
1	PT.ISBS	0.11	6	100	0.818	0.833	0.800	0.184	0.127	0.132	0.120	0.057	0.052	0.064
2	PT.MS	0.09	5	90	1.000	1.000	0.889	0.039	0.039	0.039	0.000	0.000	0.000	0.039
3	PT.CBS	0.105	6	100	0.857	0.833	0.800	0.171	0.127	0.118	0.106	0.044	0.053	0.065
4	PT.JCT	0.1	6	80	0.900	0.833	1.000	0.092	0.059	0.035	0.092	0.033	0.057	0.000
	Weight(w_j^c)											0.290	0.349	0.361

3.3. Supplier Evaluation

Five decision-makers evaluated the suppliers as experts following the predetermined criteria; the results are summarized in Table 10. The geometric mean of the fuzzy initial decision matrix is employed to construct the initial matrix, as illustrated in Table 11. The subsequent phase entails the development of an extended initial fuzzy matrix (see Table 12). The extension involves the identification of the fuzzy ideal and fuzzy anti-ideal solutions. The third stage consists of normalizing the data to guarantee its awareness. The results of the normalization procedure are summarized in Table 13.

Following the normalization of the initial matrix, the aggregated values are calculated in the fourth step utilizing the weighting coefficients derived from the preceding phase. The fourth step's result is in Table 14. The calculation of the fuzzy utility degree takes place in the fifth step. Identifying the ideal and anti-ideal solutions was crucial for executing this step. Anti-ideal values represent the minimum acceptable level of a specific criterion, while the perfect solution indicates the maximum standard of that criterion. The utility degrees were determined by aggregating the values of each supplier in conjunction with the ideal and anti-ideal solutions. The sixth step of the F-MARCOS method involves defining the utility function of the suppliers. The utility function for the ideal and anti-ideal solutions was computed to determine this function. The final value of the suppliers was determined by incorporating these values, which established their ranking.

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Table 10. Linguistic variable and fuzzy parameter of supplier assessment

Expert		**PT.ISBS**			**PT.MS**			**PT.CBS**			**PT.JCT**		
		C_1	C_2	C_3	C_1	C_2	C_3	C_1	C_2	C_3	C_1	C_2	C_3
1	Ex_1	MG	M	EG	MG	MP	EG	M	VP	VG	G	M	VP
2	Ex_2	M	MP	EG	VG	G	G	MP	P	G	MG	VG	MP
3	Ex_3	M	MG	EG	P	MP	MG	MP	MG	EG	M	MG	G
4	Ex_4	M G	P	VP	VP	EG	EG	M	G	P	G	EG	P
5	Ex_5	EG	MP	EG	M	EG	P	VG	MG	M	MP	VG	M
Expert		**PT.ISBS**			**PT.MS**			**PT.CBS**			**PT.JCT**		
		C_1	C_2	C_3	C_1	C_2	C_3	C_1	C_2	C_3	C_1	C_2	C_3
1	Ex_1	(5,5,7)	(3,5,5)	(7,9,9)	(5,5,7)	(3,3,5)	(7,9,9)	(3,5,5)	(1,1,3)	(7,7,9)	(5,7,7)	(3,5,5)	(1,1,3)
2	Ex_2	(3,5,5)	(3,3,5)	(7,9,9)	(7,7,9)	(5,7,7)	(5,7,7)	(3,3,5)	(1,3,3)	(5,7,7)	(5,5,7)	(7,7,9)	(3,3,5)
3	Ex_3	(3,5,5)	(5,5,7)	(7,9,9)	(1,3,3)	(3,3,5)	(5,5,7)	(3,3,5)	(5,5,7)	(7,9,9)	(3,5,5)	(5,5,7)	(5,7,7)
4	Ex_4	(5,5,7)	(1,3,3)	(1,1,3)	(1,1,3)	(7,9,9)	(7,9,9)	(3,5,5)	(5,7,7)	(1,3,3)	(5,7,7)	(7,9,9)	(1,3,3)
5	Ex_5	(7,9,9)	(3,3,5)	(7,9,9)	(3,5,5)	(7,9,9)	(1,3,3)	(7,7,9)	(5,5,7)	(3,5,5)	(3,3,9)	(7,7,9)	(3,5,5)
Expert		**PT.ISBS**			**PT.MS**			**PT.CBS**			**PT.JCT**		
		C_4	C_6	C_7	C_4	C_6	C_7	C_4	C_6	C_7	C_4	C_6	C_7
1	Ex_1	M	MG	EG	P	MP	MG	M	M	EG	M	MG	G
2	Ex_2	M G	P	VP	VP	EG	EG	M	G	P	VG	VG	VP
3	Ex_3	EG	MP	EG	M	EG	P	VG	MG	M	MP	VG	M
4	Ex_4	M	MP	EG	EG	MG	MG	MP	P	G	MG	VG	MP
5	Ex_5	G	MP	VG	MG	MP	EG	M	VP	VG	G	M	VP
Expert		**PT.ISBS**			**PT.MS**			**PT.CBS**			**PT.JCT**		
		C_4	C_6	C_7	C_4	C_6	C_7	C_4	C_6	C_7	C_4	C_6	C_7
1	Ex_1	(3,5,5)	(5,5,7)	(7,9,9)	(1,3,3)	(3,3,5)	(5,5,7)	(3,5,5)	(3,5,5)	(7,9,9)	(3,5,5)	(5,5,7)	(5,7,7)
2	Ex_2	(5,5,7)	(1,3,3)	(1,1,3)	(1,1,3)	(7,9,9)	(7,9,9)	(3,5,5)	(5,7,7)	(1,3,3)	(7,7,9)	(7,7,9)	(1,1,3)
3	Ex_3	(7,9,9)	(3,3,5)	(7,9,9)	(3,5,5)	(7,9,9)	(1,3,3)	(7,7,9)	(5,5,7)	(3,5,5)	(3,3,9)	(7,7,9)	(3,5,5)
4	Ex_4	(3,5,5)	(3,3,5)	(7,9,9)	(7,9,9)	(5,5,7)	(5,5,7)	(3,3,5)	(1,3,3)	(5,7,7)	(5,5,7)	(7,7,9)	(3,3,5)
5	Ex_5	(5,7,7)	(3,3,5)	(7,7,9)	(5,5,7)	(3,3,5)	(7,9,9)	(3,5,5)	(1,1,3)	(7,7,9)	(5,7,7)	(3,5,5)	(1,1,3)

Table 11. Initial matrix of the F-MARCOS

Supplier	C_1			C_2			C_3		
	n_1	n_2	n_3	n_1	n_2	n_3	n_1	n_2	n_3
PT.ISBS	4.36	5.62	6.43	2.67	3.68	4.83	4.74	5.80	7.22
PT.MS	2.54	3.50	4.90	4.66	5.52	6.77	4.15	6.11	6.53
PT.CBS	3.55	4.36	5.62	2.63	3.50	4.99	3.74	5.81	6.11
PT.JCT	4.08	5.16	6.12	5.52	6.43	7.61	2.14	3.16	4.36
Supplier	C_4			C_6			C_7		
	n_1	n_2	n_3	n_1	n_2	n_3	n_1	n_2	n_3
PT.ISBS	4.36	6.02	6.43	2.67	3.32	4.83	4.74	5.52	7.22
PT.MS	2.54	3.68	4.90	4.66	5.16	6.77	4.15	5.71	6.53
PT.CBS	3.55	4.83	5.62	2.37	3.50	4.66	3.74	5.81	6.11
PT.JCT	4.36	5.16	6.43	5.52	6.12	7.61	2.14	2.54	4.36

Table 12. Extended initial matrix of the F-MARCOS

Supplier	C_1			C_2			C_3		
	n_1	n_2	n_3	n_1	n_2	n_3	n_1	n_2	n_3
A_{AI}	2.54	3.50	4.90	2.63	3.50	4.83	2.14	3.16	4.36
PT.ISBS	4.36	5.62	6.43	2.67	3.68	4.83	4.74	5.80	7.22
PT.MS	2.54	3.50	4.90	4.66	5.52	6.77	4.15	6.11	6.53
PT.CBS	3.55	4.36	5.62	2.63	3.50	4.99	3.74	5.81	6.11
PT.JCT	4.08	5.16	6.12	5.52	6.43	7.61	2.14	3.16	4.36
A_{ID}	4.36	5.62	6.43	5.52	6.43	7.61	4.74	6.11	7.22
Supplier	C_4			C_6			C_7		
	n_1	n_2	n_3	n_1	n_2	n_3	n_1	n_2	n_3
A_{AI}	2.54	3.68	4.90	2.37	3.32	4.66	2.14	2.54	4.36
PT.ISBS	4.36	6.02	6.43	2.67	3.32	4.83	4.74	5.52	7.22
PT.MS	2.54	3.68	4.90	4.66	5.16	6.77	4.15	5.71	6.53
PT.CBS	3.55	4.83	5.62	2.37	3.50	4.66	3.74	5.81	6.11
PT.JCT	4.36	5.16	6.43	5.52	6.12	7.61	2.14	2.54	4.36
A_{ID}	4.36	6.02	6.43	5.52	6.12	7.61	4.74	5.81	7.22

Table 13. Normalized extended initial matrix of the F-MARCOS

Supplier	C_1			C_2			C_3		
	n_1	n_2	n_3	n_1	n_2	n_3	n_1	n_2	n_3
A_{AI}	0.39	0.45	0.58	0.35	0.41	0.48	0.30	0.35	0.45
PT.ISBS	0.39	0.45	0.58	0.54	0.71	0.98	0.30	0.37	0.45
PT.MS	0.52	0.72	1.00	0.39	0.48	0.56	0.33	0.35	0.52
PT.CBS	0.45	0.58	0.71	0.53	0.75	1.00	0.35	0.37	0.57
PT.JCT	0.41	0.49	0.62	0.35	0.41	0.48	0.49	0.68	1.00
A_{ID}	0.52	0.72	1.00	0.54	0.75	1.00	0.49	0.68	1.00
Supplier	C_4			C_6			C_7		
	n_1	n_2	n_3	n_1	n_2	n_3	n_1	n_2	n_3
A_{AI}	0.39	0.57	0.76	0.31	0.44	0.61	0.30	0.35	0.60
PT.ISBS	0.68	0.93	1.00	0.35	0.44	0.63	0.66	0.76	1.00
PT.MS	0.39	0.57	0.76	0.61	0.68	0.89	0.57	0.79	0.90
PT.CBS	0.55	0.75	0.87	0.31	0.46	0.61	0.52	0.80	0.85
PT.JCT	0.68	0.80	1.00	0.73	0.80	1.00	0.30	0.35	0.60
A_{ID}	0.68	0.93	1.00	0.73	0.80	1.00	0.66	0.80	1.00

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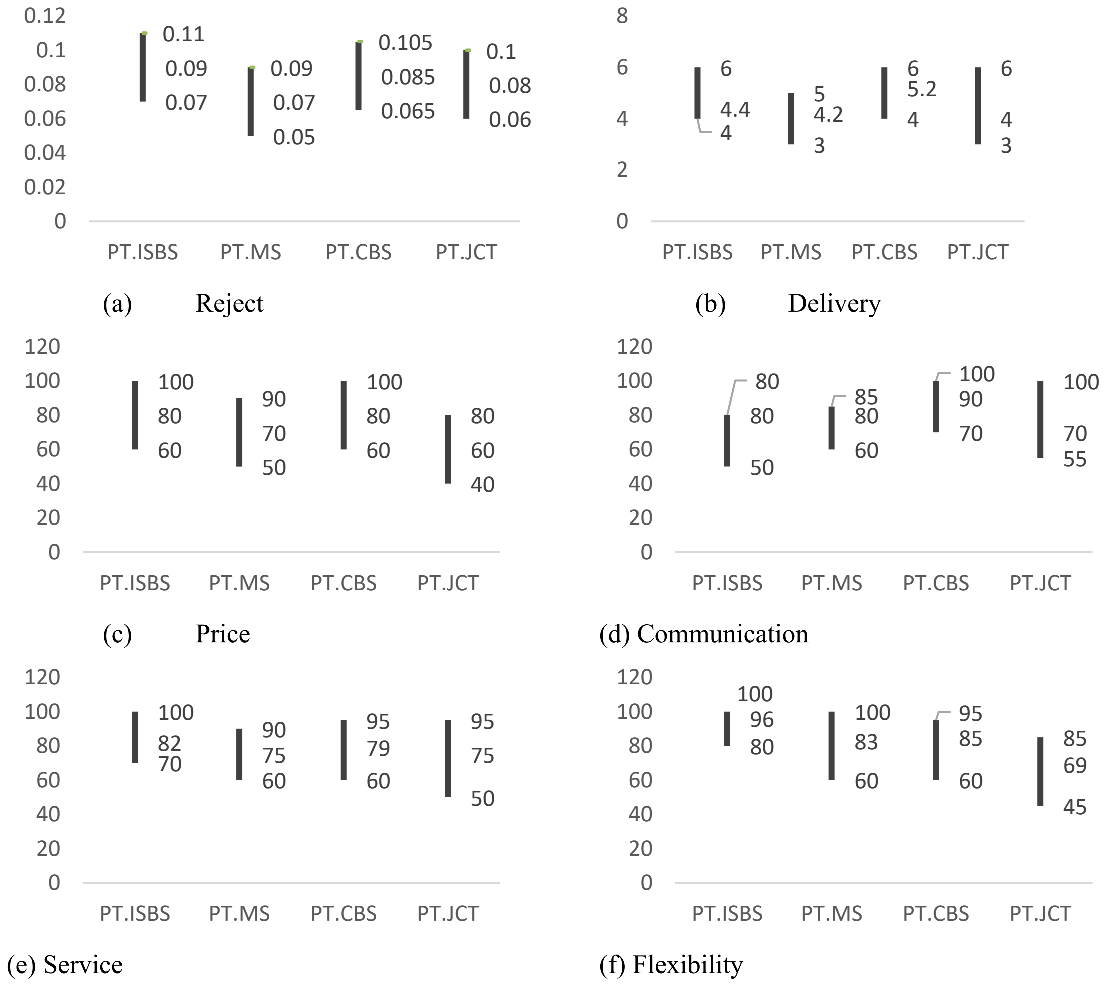
Table 14. Weighted by the normalized extended initial matrix

Supplier	C_1			C_2			C_3		
	n_1	n_2	n_3	n_1	n_2	n_3	n_1	n_2	n_3
A_{AI}	0.39	0.45	0.58	0.35	0.41	0.48	0.30	0.35	0.45
PT.ISBS	0.39	0.45	0.58	0.54	0.71	0.98	0.30	0.37	0.45
PT.MS	0.52	0.72	1.00	0.39	0.48	0.56	0.33	0.35	0.52
PT.CBS	0.45	0.58	0.71	0.53	0.75	1.00	0.35	0.37	0.57
PT.JCT	0.41	0.49	0.62	0.35	0.41	0.48	0.49	0.68	1.00
A_{ID}	0.52	0.72	1.00	0.54	0.75	1.00	0.49	0.68	1.00
Supplier	C_4			C_6			C_7		
	n_1	n_2	n_3	n_1	n_2	n_3	n_1	n_2	n_3
A_{AI}	0.39	0.57	0.76	0.31	0.44	0.61	0.30	0.35	0.60
PT.ISBS	0.68	0.93	1.00	0.35	0.44	0.63	0.66	0.76	1.00
PT.MS	0.39	0.57	0.76	0.61	0.68	0.89	0.57	0.79	0.90
PT.CBS	0.55	0.75	0.87	0.31	0.46	0.61	0.52	0.80	0.85
PT.JCT	0.68	0.80	1.00	0.73	0.80	1.00	0.30	0.35	0.60
A_{ID}	0.68	0.93	1.00	0.73	0.80	1.00	0.66	0.80	1.00

Table 15. Final value of suppliers

Supplier	K_i^-			K_i^+			$f(K_i^-)$		
	n_1	n_2	n_3	n_1	n_2	n_3	n_1	n_2	n_3
PT.ISBS	0.589	1.381	3.085	0.347	0.764	1.753	0.235	0.551	1.230
PT.MS	0.574	1.349	3.050	0.338	0.746	1.733	0.229	0.538	1.216
PT.CBS	0.553	1.376	3.062	0.326	0.761	1.740	0.220	0.549	1.221
PT.JCT	0.629	1.432	3.288	0.371	0.792	1.868	0.251	0.571	1.311

Supplier	$f(K_i^+)$			$K_{i\ crisp}^-$	$K_{i\ crisp}^+$	$f(K_i^-)_c$	$f(K_i^+)_c$	$f(K_i\ )_{cri}$	Rank
	n_1	n_2	n_3						
PT.ISBS	0.138	0.305	0.699	1.533	0.859	0.611	0.343	0.81941	2
PT.MS	0.135	0.297	0.691	1.503	0.843	0.599	0.336	0.7878	4
PT.CBS	0.130	0.303	0.693	1.520	0.852	0.606	0.340	0.80528	3
PT.JCT	0.148	0.316	0.745	1.608	0.901	0.641	0.359	0.90114	1



(a) Reject

(b) Delivery

(c) Price

(d) Communication

(e) Service

(f) Flexibility

Figure 3. Performance of the suppliers.

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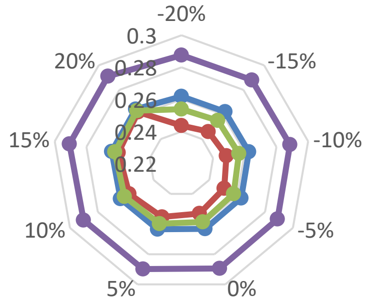
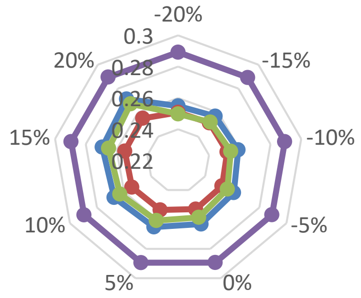
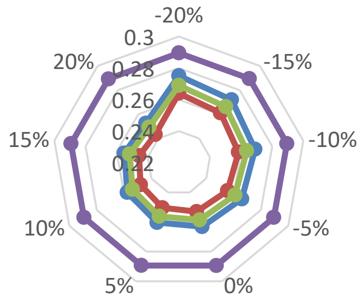


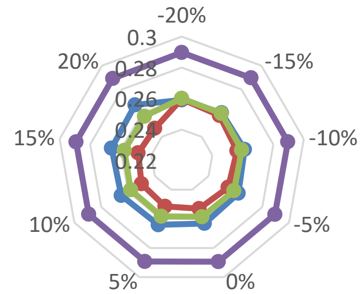
(a) Reject



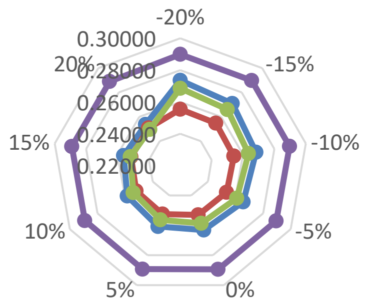
(b) Delivery



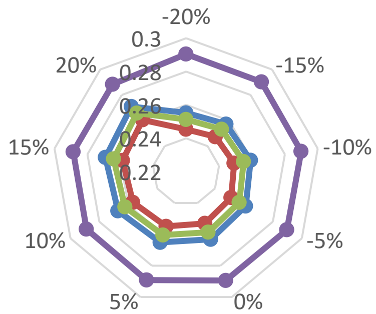
(c) Price



(d) Communication



(e) Service



(f) Flexibility

Figure 4. Sensitivity analysis.

3.2. Discussion

The ranking of supplier evaluation for PT. Wika Beton is PT. JCT, PT. ISBS, PT. CBS, and PT. MS. The weight of the criteria and supplier performance determines this evaluation. The crisp values after normalization for the weights of reject, delivery, price, communication, service, and flexibility are 0.159, 0.134, 0.204, 0.204, 0.174, and 0.126, respectively. If associated with supplier performance, as seen in Figures 3(c) and 3(d), PT. JCT has the lowest price compared to others; likewise, for the performance of the communication sector, PT. JCT has a relatively higher performance value than others. At the same time, the weight of the price and communication criteria is the largest, making PT. JCT is the best supplier candidate. The weight of the reject and delivery criteria is only fourth and fifth, so their contribution is not the most significant. However, based on Figures 3(a) and 3(b), PT JCT's reject and delivery performance is excellent. In general, PT.JCT performs well in all criteria except flexibility, with the lowest weight of the flexibility criteria. Even the performance of the price criteria is the best, with the highest weight of the price criteria. So, the proposed method is the best one for providing the best alternative for PT. Wika Beton is determining suppliers to increase its production.

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Moreover, managers should emphasize considerations beyond cost, which have been overshadowed due to the product's critical role in the organization's survival and elevated demand. The production process should function efficiently by emphasizing the reject and delivery criteria. Therefore, besides the lowest price, the supplier exhibiting the quickest delivery time and lowest rejection should be prioritized and regarded as the optimal choice, regardless of their performance in other domains.

A sensitivity analysis is needed to validate the proposed method, with changes for each weight range from -5% to 20%. Based on Figure 4, the proposed method is not sensitive to changes in the criteria weight because the supplier ranking does not change. So, the proposed method is valid. Based on Figures 4.b and 4.d, changes in the delivery and communication criteria weight will start to cause changes in the second and third supplier rankings if they are below 20%. Meanwhile, changes in the weight of the reject and service criteria will start to cause changes in the second and third supplier rankings if they exceed 20% (see Figures 4(a) and 4(e)). Based on Figures 4.c and 4.f, regardless of the change in the weight of the price and flexibility criteria, it does not affect the supplier ranking.

Table 16. Supplier rank for each hybrid MARCOS method

Supplier	MARCOS (Stević et al. [2], Paradowski and Szyjewski [10])		F SWARA MARCOS (Tadić et al. [21])		F-MARCOS (Ecer and Pamucar [22])		F-SWARA F-MARCOS (Tus and Aytac-Adali [8])		Proposed method	
	Utility function	Rank	Utility function	Rank	Utility function	Rank	Utility function	Rank	Utility function	Rank
PT.ISBS	0.7504	2	0.7524	2	0.8070	1	0.9654	3	0.8194	2
PT.MS	0.7435	3	0.7491	3	0.7782	3	0.9488	2	0.7878	4
PT.CBS	0.7869	1	0.7904	1	0.8057	2	0.9774	1	0.8053	3
PT.JCT	0.7202	4	0.7205	4	0.7756	4	0.9294	4	0.9011	1

Table 17. Borda count for each performance's selected supplier

Crite ria		MARCOS (Stević et al. [2], Paradowski and Szyjewski [10]) - PT.CBS	F SWARA MARCOS (Tadić et al. [21]) - PT.CBS	F-MARCOS (Ecer and Pamucar [22]) - PT.ISBS	F-SWARA F-MARCOS (Tus and Aytac-Adali [8]) - PT.CBS	Proposed method - PT.JCT
C_1	Performance	0.065	0.065	0.07	0.065	0.06
	Rank	2	2	3	2	1
	Borda	3	3	1	3	5
C_2	Performance	4	4	4	4	3
	Rank	2	2	2	2	1
	Borda	2.5	2.5	2.5	2.5	5
C_3	Performance	60	60	60	60	40
	Rank	2	2	2	2	1
	Borda	2.5	2.5	2.5	2.5	5
C_4	Performance	100	100	80	100	100
	Rank	1	1	2	1	1
	Borda	3.5	3.5	1	3.5	3.5
C_6	Performance	60	60	70	60	50
	Rank	2	2	1	2	3
	Borda	3	3	5	3	1
C_7	Performance	60	60	80	60	45
	Rank	2	2	1	2	3
	Borda	3	3	5	3	1
	Sum	17.5	17.5	17	17.5	20.5

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Table 16 compares the supplier's utility function and the rank of the methods. It shows that the supplier rank for each technique is different. Meanwhile, supplier selection aims to select the supplier with the best performance in each criterion. Often, no single supplier performs best across all of these criteria. So, MCDM is needed to solve this problem. The proposed method is compared with the previous methods to determine its effectiveness. This test uses the Borda count on the performance of selected suppliers for each method. The Borda count generates the overall ranking of suppliers by combining inconsistent results from different evaluation models [23]. The Borda rule suits multi-person decision-making when exploring multiple options [23]. In other words, the Borda technique assigns ranks to alternatives based on the assumption that the higher an option's position on the list, the higher its rating. The winner is the option with the highest calculated score, where each alternative is awarded a score beginning with 1 for the least favorable answer, 2 for the second worst, 3 for the third worst, and so on. The Borda score for each option is calculated by weighting all scores [23]Figure 2 shows each supplier's performance for each criterion. Table 17 shows the test results. Based on Table 18, the supplier of the proposed method has the highest Borda value. Thus, the proposed method is more effective than the previous method because it can select the supplier with the best performance.

4. CONCLUSION

The optimal raw material supplier for the Indonesian concrete industry was determined by material quality, competitive pricing, prompt delivery, communication, service, and flexibility. PT JCT emerged as the optimal choice, exhibiting a utility value of 0.9011. PT Wika Beton places significant emphasis on the quality of raw materials and prompt delivery. The company strategically selects raw materials at competitive prices, aligning with its cost-cutting initiatives in the supply chain to ensure customer satisfaction and maintain high service quality.

The decision to select PT JCT as the optimal supplier is justified and sound. Cost is traditionally viewed as a critical factor, often leading to immediate rejection, while other aspects are evaluated with varying degrees of importance. In Indonesia, concrete products play a crucial role in infrastructure development, and managers are responsible for ensuring the operational efficiency of their production. The sustainability of the Indonesian concrete industry is contingent upon the selection of suppliers. Selecting an appropriate supplier enhances a concrete manufacturing company's downstream operation by decreasing production costs and improving customer satisfaction.

The company in the case study experienced a 5% reduction in production costs in the later stages of the project, following several months of implementation, indicating the effectiveness of the proposed methodology. The management of the case companies is fully committed to executing the supplier ranking established in this study and allocating orders according to that ranking. This commitment demonstrates their confidence in the proposed methodology's effectiveness.

The future research: (1) consider applications in other industries; (2) the use of Deep Reinforcement Learning (DRL) in optimal supplier selection in dynamic environments; (3) the use of Machine Learning models, such as Random Forest, or Neural Networks to predict supplier performance based on historical data; (4) the use of AI to automatically determine criteria weights; (5) the use of Fuzzy Logic accompanied by AI to handle uncertainty in decision-maker preferences.

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