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Research article

Power equipment supplier evaluation under a q-rung orthopair fuzzy set based decision making model

Jiawei Mao [a], JinGuo Huang [a], Jing Liu [a,*], Chao Peng [b], ShiZe Zhang [b]

[a] School of Mechanical Science and Engineering, Huazhong University of Science and Technology, No. 1037, Juy Road, Hongshan District, Wuhan, 430074, China

[b] China Electrical Power Research Institute, Wuhan, Hubei, 430074, China

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ABSTRACT

The quality performance of power equipment suppliers is directly related to the stable and safe operation of the grid. This study presents a decision-making model based on q-rung orthopair fuzzy sets (q-ROFS) to evaluate suppliers, focusing on quality as the key criterion. To assess the objectivity and comprehensiveness of the results, we provide an innovative information fusion method that integrates the four dimensions of supply risk, supplier quality capability, profit impact, and willingness into the decision-making process. Considering the uncertainty and inconsistency in the decision-making process, in the weight determination stage, the q-ROFS-FWZIC method is used as the standard to allocate weights accurately. In the ranking stage, the q-ROFS-MABAC method was constructed to improve the consistency of evaluation results, and suppliers were ranked based on summarized performance data. A real-world case study involving power transformer suppliers illustrates the effectiveness of the proposed model. This research offers valuable insights for decision-makers in the power sector to optimize supplier selection, improve quality control measures, and ensure the ongoing reliability of the grid. Furthermore, this method can also be extended to other fields to solve various MCDM problems.

1. Introduction

The power grid is one of the most representative applications of the electrical power system [1]. In recent years, the power sector, as a key national industry, has experienced significant growth. The power grid has continuously expanded, and the variety of equipment has become increasingly diverse [2]. Electricity constitutes a significant portion of a country's economy [3]. Therefore, all equipment within the power system must operate at the highest possible efficiency and prevent accidents from occurring [4]. When power equipment fails, the distribution network operation encounters problems, leading to increased operational costs of the power grid and reduced reliability of power delivery. Approximately 4 %–5 % of the total cost of the power system is allocated to protecting equipment [5]. However, there is currently a lack of a comprehensive evaluation system for power equipment suppliers that spans the entire lifecycle. This gap leads to issues such as poor-quality control in equipment management, increased pressure on the safe operation of equipment, and ineffective feedback on equipment performance in the network bidding process [6]. Ensuring high-quality equipment suppliers is crucial for Grid Corporation and the power-consuming world.

Supplier evaluation strategies usually emphasize selecting suppliers who provide cost-effective products with acceptable quality

* Corresponding author.
E-mail address: Jingliu_HUST@163.com (J. Liu).

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[7]. It is defined as the process of measuring supplier performance [8]. The power grid is a complex and interconnected system, with the State Grid Corporation of China (SGCC) serving 88 % of China's territory [9]. Its operational goal is to provide high-quality electrical energy with low-cost and high-quality equipment. Currently, most supplier evaluations emphasize overall supplier performance, where quality is regarded as a critical factor. Studies indicate that quality is a primary factor in selecting equipment suppliers [10,11], as suppliers significantly influence the final product's quality [12]. Consequently, developing a comprehensive evaluation system for power equipment suppliers is crucial to assist SGCC in selecting top-quality suppliers.

The motivation behind this study stems from SGCC's increasing awareness that supplier evaluation is crucial not only during operation and maintenance phases but throughout the entire lifecycle of equipment. There is a growing emphasis on equipment quality in supplier evaluation within the field of supply chain management [13]. Against this backdrop, SGCC has initiated comprehensive quality management throughout the lifecycle of power equipment. This study specifically addresses the supplier evaluation challenges faced by SGCC, adopting a quality-focused approach. The supplier quality standards consider a lifecycle quality perspective, encompassing production manufacturing quality, transportation and storage quality, construction and installation quality, and operation and maintenance quality.

The proposed model for evaluating power equipment suppliers is determined as a q-ROFS-FWZIC-MABAC hybrid method. The first-stage model aims to construct supplier evaluation criteria. Building upon material quality assessments conducted at the Electrical Supply Chain Operations Center (ESC), a review of the literature on power equipment supplier evaluation was conducted. Experts from China Electric Power Research Institute determined key criteria, considering a quality assessment framework across four dimensions: Supply Risk (SR), Profit Impact (PI), Supplier Willingness (SW), and Supplier Quality Capability (SQC). The q-rung orthopair fuzzy set-based Fuzzy Weighted Zero Inconsistency (q-ROFS-FWZIC) method was employed to determine the weights assigned to each evaluation criterion.

The second stage aims to utilize the q-ROFS-based multi-attribute border approximation area comparison (MABAC) method. By integrating the evaluation criteria weights obtained in the first stage and performance data extracted from ESC across four dimensions, it calculates the final scores of suppliers and provides the ultimate evaluation results. The introduction of q-ROFS addresses the fuzziness and uncertainty in the decision-making process of supplier evaluation [14]. Unlike traditional Multi-Criteria Decision Making (MCDM) methods, this approach integrates the FWZIC model and MABAC model, utilizing lifecycle quality data of power equipment as the evaluation data for Supplier Quality Capability (SQC). Therefore, through these two-stage models, the overall lifecycle quality of power equipment can be enhanced, improving the accuracy of supplier assessment results.

This study contributes in four main aspects.

1. We researched supplier evaluation based on lifecycle quality data of power equipment, expanding the current focus on power equipment supplier evaluation to include four dimensions: SR, PI, SQC, and SW. We developed a comprehensive evaluation framework for power equipment suppliers.
2. The model introduced a hybrid approach combining q-rung-FWZIC and q-rung-MABAC methods for supplier evaluation regarding the lifecycle quality of power equipment, enriching the methodological literature on power equipment supplier evaluation.
3. Through the integration of q-rung fuzzy sets, this model effectively tackles and reduces the typical uncertainties and inaccuracies encountered in real-world decision-making scenarios. This highlights the importance and practical use of fuzzy logic techniques in the decision-making process.
4. We applied the hybrid model for supplier evaluation, which demonstrates higher accuracy compared to traditional MCDM methods and considers information uncertainty. The proposed method's effectiveness and robustness were validated through practical application in evaluating power transformer suppliers.

The rest of this paper is organized as follows: Section 2 presents a literature review, while Section 3 discusses the problem formulation. The proposed method is detailed in Section 4. Section 5 covers case studies and sensitivity analyses to validate the results. Results and discussions are provided in Section 6, with conclusions in Section 7.

2. Literature review

Our work intersects primarily with the fields of power equipment supplier evaluation and MCDM methods. Here, we review the latest research in these two domains.

2.1. Evaluation of power equipment suppliers

Electricity, as the core hub of the energy industry, has garnered attention in the evaluation of equipment suppliers [15]. Research on supplier selection indicators for power equipment remains inconclusive. Many studies on supplier evaluation focus on MCMD methods and managing uncertainty [16–18]. Most literature primarily focuses on assessing the overall performance of suppliers [19]. With the advocacy for green energy, some scholars have recently focused more on the green performance of suppliers [20]. However, few scholars have prioritized quality-focused evaluations of power equipment suppliers. Xiong et al. assessed and ranked suppliers using sampling inspection data from power cables, introducing an evaluation method that combines entropy weights with the analytic hierarchy process [21]. Min-Chih Hsu et al. from a holistic perspective, applied the AHP-IFNs-DEMATEL to establish a supplier selection model for offshore wind energy companies [22]. Chen et al. extracted distribution transformer (DT) supplier data from ECP and used the Entropy Method to evaluate DT suppliers [23]. Van et al. created a decision-making model employing spherical fuzzy sets to choose wind turbine suppliers for wind power projects [24]. Table 1 summarizes important literature for evaluating power equipment suppliers, and the main characteristics of our study are shown in the last row.

Table 1 indicates that existing studies on power equipment supplier evaluation mostly employ MCDM models in fuzzy environments, with the Analytic Hierarchy Process (AHP) being the primary method for determining weights, and some studies using data analytics models. Additionally, from the literature review above, it is evident that previous evaluation criteria for power equipment suppliers have mostly been derived from literature reviews or expert opinions, without forming a unified evaluation indicator system. The focus of evaluation has primarily been on overall supplier performance. However, quality is crucial for ensuring that suppliers deliver products or services that meet required standards and specifications [31]. As mentioned earlier, SGCC conducts comprehensive quality control over the entire life-cycle of power equipment, emphasizing evaluations aimed at quality improvement or development of suppliers. Based on this analysis, this study considers the full life-cycle quality of power equipment, constructs a new set of evaluation indicators, and proposes a novel evaluation model that better meets the practical assessment needs of SGCC's daily operations.

2.2. Application of the MCDM method in supplier evaluation

MCDM methods are the primary approach for supplier evaluation [20]. However, each MCDM method has specific mathematical characteristics and different methods typically yield different results. This implies that the final choice of alternatives is influenced by both the evaluation criteria and the MCDM method used. Dragan Pamučar proposed an MCDM method called MABAC [32]. This method is a reliable rational decision-making tool. Compared to SAW, COPRAS, TOPSIS, MOORA, and VIKOR, its advantages lie in the stability of the solutions and its flexibility in combining with other methods [33]. Many scholars have applied the MABAC method to supplier evaluation, often combining it with various methods for determining weights [34,35]. Gupta, Shubham, and colleagues developed an MCDM-based framework using fuzzy AHP and MABAC, WASPAS, and TOPSIS for selecting green suppliers in the automotive industry [36]. Mohamed Abdel-Basset and colleagues developed a MABAC method incorporating BWM, plithogenic set, and rough numbers to evaluate and select the optimal suppliers in the healthcare industry [37].

The method of determining weights directly affects the evaluation results. As shown in Table 1, currently, AHP, fuzzy AHP, DEMATEL, and BWM are commonly used in supplier evaluations. Mohammed et al. introduced the FWZIC method, which assigns weights to criteria with zero inconsistency [38]. This method overcomes certain limitations of BMW and AHP [39]. However, this method cannot effectively resolve issues of uncertainty and fuzziness. Zadeh first proposed the concept of Fuzzy Sets (FS), which conveniently express MADM and MAGDM problems [40]. Krassimir introduced the theory of Intuitionistic Fuzzy Sets (IFS) [41], and Yager introduced Pythagorean Fuzzy Sets (PFS), which generalize FS and IFS [42]. PFS can address various issues that IFS cannot handle in specific practical scenarios. To further enhance these capabilities, Yager introduced the concept of q-Rung Orthopair Fuzzy Sets (q-ROFS), building on IFS and PFS, to better manage uncertainty information and information aggregation [43,44]. Recent studies have highlighted the importance of q-ROFS decision-making methods [45]. Chao Zhang proposed A novel multi-granularity three-way decision-making approach in q-rung orthopair fuzzy information systems [46]. Those grounded in granular computing strategies offer enhanced mechanisms to manage uncertainty and fuzziness in decision-making [47].

Summing up the above literature, we have the following findings. Numerous studies have utilized MABAC for supplier evaluation to improve the consistency of evaluation results. Various types of fuzzy sets have been utilized to handle uncertainties in the decision-making process. When constructing the MABAC model, most scholars use methods like AHP and BWM, while few have adopted the FWZIC method. Additionally, there is limited research that combines the q-rung fuzzy sets with the FWZIC method to ensure the accuracy of evaluation results. Therefore, establishing an MCDM model that integrates FWZIC and MABAC, and uses q-ROFS to express decision-making information, will help enhance the accuracy of evaluation results. This approach has not yet been applied in the field of power equipment supplier evaluation.

3. Problem formulation

State Grid Corporation of China (SGCC) has established a modern intelligent supply chain system centered around the E-Commercial Platform (ECP), Electrical Equipment Intelligent IoT Platform (EIP), Electrical Logistics Service Platform (ELP), Enterprise Resource Management System (ERP), and Power Production Management System (PMS) [48], as well as the Electrical Supply Chain Operation Center (ESC) system. ESC stores and manages vast amounts of historical data sourced from ECP, ERP, ELP, and PMS systems. Specifically, the ECP platform aggregates extensive sampling data, the EIP platform collects production process data and factory inspection data from suppliers, the ELP platform gathers logistics and warehouse information related to grid equipment, and the PMS platform contains essential operational and maintenance data for grid equipment, as depicted in Fig. 1. Based on this extensive and diverse historical data, the SQC standards are explored from perspectives such as quality, economic impact of quality, and quality variability.

The data utilized in this study were sourced from multiple systems within the ESC. Due to the confidential nature of the grid system and data security protocols, the exact preprocessing steps for the q-rung orthopair fuzzy data cannot be disclosed in detail. However, the data were processed by standard practices for handling incomplete, imprecise, and uncertain data in a fuzzy environment. The preprocessing ensured the data's consistency, accuracy, and suitability for use within the q-rung orthopair fuzzy decision-making framework, while also adhering to all necessary confidentiality requirements.

With the rapid increase in electricity demand and the expansion of equipment scale, SGCC is increasing its investment in grid security. In this study, to test the proposed model, we analyzed the transformer supplier evaluation. Based on the existing evaluations of power equipment suppliers and the standards obtained from the literature review, we contacted experts from the China Electric

Table 1
The main characteristics of the power equipment supplier evaluation literature and our study.

Study	Methods	Fuzzy Environment	Criteria	Case	overall performance	quality performance
[20]	Fuzzy-ANP-TOPSIS	TNF	5 criteria and 15 sub-criteria	Wind turbine supplier evaluation	YES	/
[21]	Entropy weight-analytic hierarchy process	/	3 criteria	Power cable supplier evaluation	YES	/
[22]	AHP-IFNs-DEMATEL	TNF	23 criteria	Submarine cable supplier evaluation	YES	/
[23]	Entropy	/	4criteria and 13 sub-criteria	Distribution transformer supplier evaluation	YES	/
[24]	SF-AHP-WASPAS	Spherical Fuzzy	4 criteria and 11 sub-criteria	Wind turbine supplier evaluation	YES	/
[25]	Fuzzy-Entropy-TOPSIS	Fuzzy	5 criteria	Thermal power equipment supplier evaluation	YES	/
[26]	efficiency coefficient method	/	4 criteria and 12 sub-criteria	Power transformers supplier evaluation	YES	/
[27]	fuzzy AHP	Fuzzy	2 criteria and 8 sub-criteria	Transformer oil monitoring device supplier evaluation	YES	/
[28]	matter-element extension evaluation model	/	5 criteria and 21 sub-criteria	Wind power generation equipment supplier evaluation	YES	/
[29]	ANP-TODIM	Z-Number	6 criteria	nuclear-grade cable supplier evaluation	YES	/
[30]	HFL-TOPSIS	Hesitant Fuzzy	25 criteria	hydroelectric plant bulb-type generator unit supplier evaluation	YES	/
Our Study	q-ROFS-FWZIC-MABAC hybrid model	q-ROFS	4 dimensions 10 criteria	Distribution transformer supplier evaluation	YES	YES

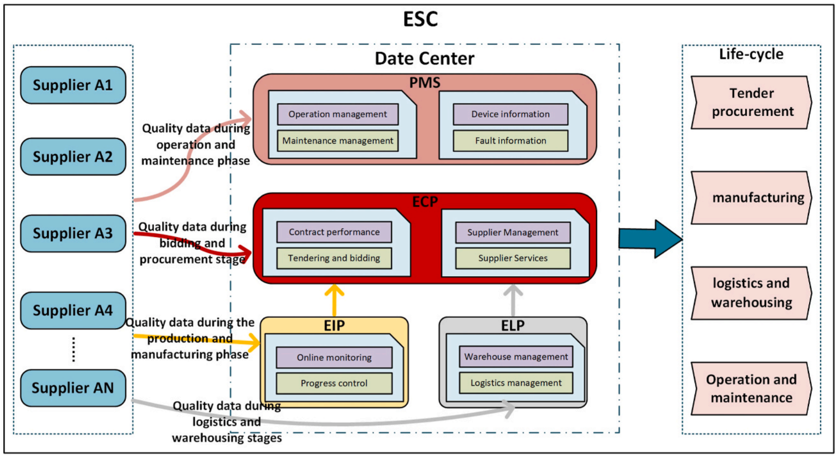

Fig. 1. ESC system architecture.

Power Research Institute via email and phone to determine the most important standards for evaluating power equipment suppliers. This led to the construction of a supplier evaluation model that covers all stages of the power equipment lifecycle (procurement, production, logistics, and maintenance). The 10 standards across four dimensions are shown in Table 2.

3.1. *Supply risk(SR)criteria*

Risk can originate from both external and internal sources within the supply chain. Proactively addressing these risks is essential for maintaining a company's productivity and vitality [49]. In this study, the SR criteria include company scale, Supply performance, and financial status.

Cr1: Enterprise Scale: Enterprise scale is a key factor to consider when selecting power equipment suppliers. The scale of an enterprise not only affects its production capacity and supply stability but also reflects its market position and reputation within the industry [23].

Cr2: Supply Performance: Delivery time and delivery punctuality are critical considerations when selecting power equipment suppliers. Any delay in the delivery of power equipment can lead to increased costs and even project failure. Additionally, the supplier's ability to successfully deliver in emergency situations should also be considered [29].

Cr3: Financial Status: Financial status is a crucial indicator for evaluating power equipment suppliers. The financial health of a supplier directly impacts its ability to sustain operations and fulfill contracts reliably. Suppliers with strong financial status can better manage production and operational risks, ensuring timely delivery of products and providing necessary after-sales services [20].

3.2. *Supplier quality capability (SQC) criteria*

Cr4: Failure Rate Per 100 Units (FPU): FPU is one of the most commonly used quality standards in the power industry, representing the failure rate per 100 units of equipment due to inherent quality issues over the past five years, as shown in Equation (1) [21].

$$FPU = \frac{\textit{five year total failure quantity}}{5^{*}\textit{total quantity}} \times 100 \tag{1}$$

Cr5: Quality Sampling Qualification Rate: Quality Sampling Qualification Rate reflects the supplier's level of product quality control during the production process and its reputation and brand image in the market. A high-quality sampling qualification rate

Table 2
Supplier quality evaluation standards.

dimensions	criteria	Data Source	Code
Supply risk(SR)	Enterprise Scale	ECP	Cr1
	Supply Performance	ECP	Cr2
	Financial Status	ECP	Cr3
Supplier Quality Capability (SQC)	Failure rate Per 100 Units	EIP, PMS	Cr4
	Quality sampling qualification rate	EIP, PMS	Cr5
	Risk Priority Number	EIP, PMS	Cr6
	Quality Fluctuation	EIP, PMS	Cr7
Profit Impact(PI)	Product Price	ECP	Cr8
Supplier Willingness (SW)	Commitment to continuous improvement in product and process(CCIPP)	EIP	Cr9
	after-sale service	EIP, PMS	Cr10

indicates that the supplier's production processes and quality management systems are well-established, resulting in higher consistency and reliability of products [50]. As shown in Equation (2).

$$SQR = \frac{number\ of\ qualified\ inspected\ devices}{total\ number\ of\ inspected\ devices} \tag{2}$$

Cr6: Risk Priority Number (RPN): FMEA is a systematic approach for identifying potential failure modes and assessing their impacts on events. The risk associated with each failure mode is quantified using the Risk Priority Number (RPN), as shown in Equation (3) [31].

$$RPN = S^{*}O^{*}D(3)$$

Where S= Severity, O= Occurrence, D = Detection factors.

Cr7: Quality Fluctuation: While quality issues may be unavoidable, severe fluctuations in quality are intolerable for the power grid. This fluctuation is a unique characteristic compared to other dimensions of standards. The same equipment from the same supplier may exhibit significant inconsistencies across different life-cycle stages. Therefore, we measure this variability using the variance within each life-cycle stage, as represented by Equation (4).

$$QF = Var(FPU) \tag{4}$$

3.3. Profit Impact(PI)criteria

Profit impact is defined as "the percentage of purchase volume, total procurement cost, and its influence on product quality or competitive strategy." [51].

Cr8: Product Price: As competition intensifies, suppliers need to provide products with a competitive pricing strategy. This doesn't necessarily mean offering the lowest price. Competitive pricing should guarantee timely delivery of the required products with the appropriate quality and quantity [52].

3.4. Supplier Willingness (SW)criteria

Supplier willingness refers to the confidence, commitment, and motivation of suppliers to build and maintain long-term relationships with buyers [53].

Cr9: CCIPP: It reflects the supplier's attitude and capability to continually pursue excellence, enhance efficiency, and improve quality in both product and process. Continuous improvement not only enhances the technical level and reliability of products but also optimizes production processes, reduces costs, and increases customer satisfaction.

Cr10: After-sale service: After-sale service is a critical consideration when selecting power equipment suppliers. High-quality after-sales service ensures smooth equipment operation, minimizes downtime, enhances customer satisfaction, and lays the foundation for long-term project success. After-sales services include installation and commissioning, technical support, maintenance, spare parts supply, and troubleshooting [54].

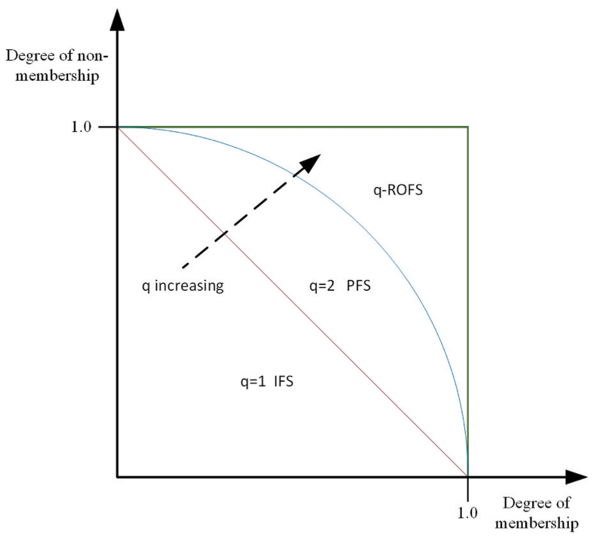

Fig. 2. q-ROFS, PFS and IFS.

4. Methodology

4.1. Q-rung fuzzy set

If we do not consider the fuzziness and uncertainty of decisions, the accuracy of evaluation results will be compromised [55]. Introducing q-ROFS can reduce the impact of fuzzy information caused by hesitations among experts. q-ROFS, introduced by Yager [56]. q-ROFSs have a broader spectrum for expressing fuzzy information compared to IFSs and PFSs, as shown in Fig. 2.

The basic concept of q-ROFS is introduced in Definition 1.

Definition 1

Let X be the universe of discourse. a q-rung orthopair fuzzy subset Q of X has given below [57]:

$$Q = \{(x, \mu_Q(x), \nu_Q(x)) | x \in X\} (5)$$

Where μ_Q : X→[0, 1] is the membership function, and ν_Q : X→[0, 1] is the non-membership function. For each element $x \in X$, satisfying Formula(6).

$$0 < (\mu_Q(x))^q + (\nu_Q(x))^q \le 1, q \ge 1 (6)$$

The degree of uncertainty is represented in Formula (7) as follows:

$$\pi_Q(x) = \sqrt[q]{1 - \mu_Q(x)^q - \nu_Q(x)^q} \tag{7}$$

Definition 2

Let $Q_1 = (\mu_{Q1}, \nu_{Q1})$ and $Q_2 = (\mu_{Q2}, \nu_{Q2})$ be q-ROFS. The basic operations of q-ROFS are shown in the following Formulas [58]:

$$Q_1 \cap Q_2 = (\boldsymbol{min}\{\mu_{Q1}, \mu_{Q2}\}, \boldsymbol{max}\{\nu_{Q1}, \nu_{Q2}\}) (8)$$

$$Q_1 \cup Q_2 = (\boldsymbol{max}\{\mu_{Q1}, \mu_{Q2}\}, \boldsymbol{min}\{\nu_{Q1}, \nu_{Q2}\}) \tag{9}$$

$$Q_1 \oplus Q_2 = \left((\mu_{Q1}{}^q + \mu_{Q2}{}^q - \mu_{Q1}{}^q \mu_{Q2}{}^q)^{\frac{1}{q}}, \nu_{Q1}\nu_{Q2} \right) \tag{10}$$

$$Q_1 \otimes Q_2 = \left(\mu_{Q1}\mu_{Q2} (\nu_{Q1}{}^q + \nu_{Q2}{}^q - \nu_{Q1}{}^q \nu_{Q2}{}^q)^{\frac{1}{q}}, \right) \tag{11}$$

$$\lambda Q = \left((1 - (1 - \mu_Q{}^q)^\lambda)^{\frac{1}{q}}, \nu_Q{}^\lambda \right), \lambda > 0 \tag{12}$$

$$Q^\lambda = \left(\mu_Q^\lambda, \left(1 - \left(1 - \nu_Q^\lambda\right)^\lambda\right)^{\frac{1}{q}} \right), \lambda > 0 \tag{13}$$

$$Q_1 \oslash Q_2 = \left(\frac{\mu_{Q1}}{\mu_{Q2}}, \sqrt{\frac{\nu_{Q1}{}^q - \nu_{Q2}{}^q}{1 - \nu_{Q2}{}^q}} \right) \text{, if} \mu_{Q1} \le \boldsymbol{min}\left\{\mu_{Q2}, \frac{\mu_{Q2}\pi_1}{\pi_2}\right\}, \boldsymbol{\nu}_{Q1} \ge \boldsymbol{\nu}_{Q2} \tag{14}$$

$$\frac{Q}{\lambda} = \left(\sqrt[q]{1 - (1 - (\mu_Q)^q)^{\frac{1}{\lambda}}}, (\nu_Q)^{\frac{1}{\lambda}} \right), \lambda > 0 \tag{15}$$

Definition 3

Let $Q_i = (\mu_{Qi}, \nu_{Qi}) (i = 1, 2, 3, \ldots, n)$ be q-ROFS. The q-rung orthopair fuzzy arithmetic mean (q-ROFA) aggregation operation is represented as follows in Formula (16) [58]:

$$q - ROFA(Q_1, Q_2, Q_3, \cdots, Q_n) = \left(1 - \left(\prod_{i=1}^{n} \left(1 - \mu_{Q_i}^q\right) \right)^{\frac{1}{q}}, \prod_{i=1}^{n} \nu_{Q_i} \right) \tag{16}$$

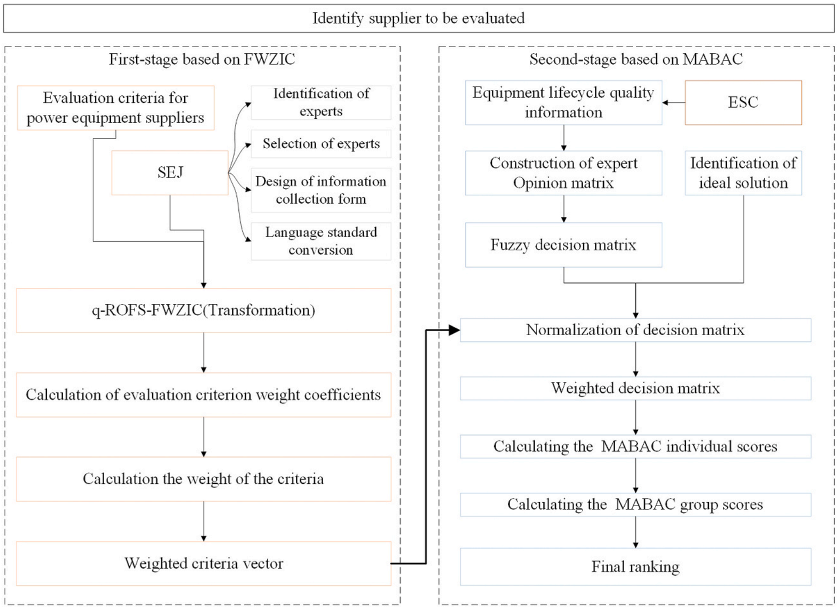

Fig. 3. Method Flowchart.

Table 3
Five-point Likert scale.

Linguistic scale	Numerical scoring scale	q-ROFS	
		M	V
Very important (VI)	1	0.95	0.15
Important (I)	2	0.75	0.35
Average (A)	3	0.55	0.55
Limited important(LI)	4	0.35	0.75
Very Low Importance (VL)	5	0.15	0.95

Table 4
Expert decision matrix.

EDM	Cr_1	Cr_2	…	Cr_n
E_1	E_1/Cr_1	E_1/Cr_2	…	E_1/Cr_n
E_2	E_2/Cr_1	E_2/Cr_2	…	E_2/Cr_n
E_3	E_3/Cr_1	E_3/Cr_2	…	E_3/Cr_n
…	…	…	…	…
E_m	E_m/Cr_1	E_m/Cr_2	…	E_m/Cr_n

Definition 4

Let $Q_i = (\mu_{Qi}, \nu_{Qi})(i = 1, 2, 3, \ldots, n)$ be q-ROFS, and let $\mathrm{w} = (\mathrm{w}_1, \mathrm{w}_2, \mathrm{w}_3, \cdots\cdots, \mathrm{w}_n)^{\mathrm{T}} \sum_{i=1}^{q} \mathrm{wi} = 1$ be the weight vector. The q-rung orthopair fuzzy weighted averaging operator (q-ROFWA) is represented as follows in Formula (17) [59]:

$$q - ROFWA(Q_1, Q_2, Q_3, \cdots, Q_n) = \left(1 - \left(\prod_{i=1}^{n} \left(1 - \mu_{Q_i}^{q}\right)^{w_i}\right)^{\frac{1}{q}}, \prod_{i=1}^{n} \nu_{Q_i}^{W_i}\right) \tag{17}$$

Definition 5

If $Q = (\mu_Q(x), \nu_Q(x))$ is a q-ROFS, the score function Score and the accuracy function h can be defined as Formula (18) and (19) respectively [58].

Table 5
q-ROFS-EDM.

Criterias/Experts	Cr_1	Cr_2	…	Cr_n
E_1	$\frac{\widetilde{E_1/Cr_1}}{\sum_{n=1}^{n}\widetilde{E_1/Cr_n}}$	$\frac{\widetilde{E_1/Cr_2}}{\sum_{n=1}^{n}\widetilde{E_1/Cr_n}}$	…	$\frac{\widetilde{E_1/Cr_n}}{\sum_{n=1}^{n}\widetilde{E_1/Cr_n}}$
E_2	$\frac{\widetilde{E_2/Cr_1}}{\sum_{n=1}^{n}\widetilde{E_2/Cr_n}}$	$\frac{\widetilde{E_2/Cr_2}}{\sum_{n=1}^{n}\widetilde{E_1/Cr_n}}$	…	$\frac{\widetilde{E_2/Cr_n}}{\sum_{n=1}^{n}\widetilde{E_2/Cr_n}}$
E_3	$\frac{\widetilde{E_3/Cr_1}}{\sum_{n=1}^{n}\widetilde{E_3/Cr_n}}$	$\frac{\widetilde{E_3/Cr_2}}{\sum_{n=1}^{n}\widetilde{E_3/Cr_n}}$	…	$\frac{\widetilde{E_3/Cr_n}}{\sum_{n=1}^{n}\widetilde{E_3/Cr_n}}$
…	…	…	…	…
E_m	$\frac{\widetilde{E_m/Cr_1}}{\sum_{n=1}^{n}\widetilde{E_m/Cr_n}}$	$\frac{\widetilde{E_m/Cr_2}}{\sum_{n=1}^{n}\widetilde{E_m/Cr_n}}$	…	$\frac{\widetilde{E_m/Cr_n}}{\sum_{n=1}^{n}\widetilde{E_m/Cr_n}}$

Table 6
Scale for criterion assessment ratings [61].

Linguistic Scale	μ_Q	ν_Q
Absolutely Low (AL)	0.15	0.95
Very Low (VL)	0.25	0.85
Low (L)	0.35	0.75
Medium Low (ML)	0.45	0.65
Equal (E)	0.55	0.55
Medium High (MH)	0.65	0.45
High (H)	0.75	0.35
Very High (VH)	0.85	0.25
Absolutely High (AH)	0.95	0.15

$$Score(Q) = \left(1 + (\mu_Q(x))^2 - (\nu_Q(x))^2\right)/2 \tag{18}$$

$$h(Q) = (\mu_Q(x))^2 + (\nu_Q(x))^2 \tag{19}$$

4.2. Q-ROFS-FWZIC-MABAC hybrid model

The proposed MCDM model in this paper combines FWZIC and MABAC. In the first part, the FWZIC method is applied in a fuzzy environment using q-ROF to calculate weights for evaluating power equipment suppliers. In the second part, based on these weights and lifecycle quality data extracted from the ESC system, the fuzzy MABAC method is employed to rank power equipment suppliers. Fig. 3 illustrates the approach proposed in this paper.

4.2.1. Q-ROFS-FWZIC method

Mohammed proposed the FWZIC method [38]. While this method has been applied to address many issues in the literature, it does not effectively resolve uncertainties and fuzziness. A.S. Albahri extended this method into the q-ROFS environment, with the steps of the q-ROFS-FWZIC method outlined as follows [60].

Step 1: The predetermined evaluation criteria for power equipment suppliers are examined, presented, classified, and categorized into two layers, as shown in the problem formulation.
Step 2: Structured expert judgment (SEJ): To assess the accuracy of the criterion weights, identify and nominate at least four domain experts, establish a structured expert judgment panel. The expert panel will utilize a Five-point Likert scale(see Table 3) to define the importance of each criterion and convert the linguistic expressions into equivalent numerical values.
Step 3: Construct Expert Decision Matrix (EDM): The EDM originates from the criteria for evaluating and selecting power equipment suppliers and the expert decision group, as shown in Table 4.
Step 4: Application of q-ROFS Membership Function: The q-ROFS membership functions and defuzzification process are applied to the EDM data, replacing the numerical scales in the EDM with q-ROFS. This step is a crucial component of the method, reducing the impact of imprecise and unclear information caused by expert hesitancy, thereby enhancing its accuracy and usability.
Step 5: Calculate the final values of the assessment criteria weights.
a) Convert the EDM to q-ROFS-EDM, where the fuzzy data ratios are computed using Formulas (7), (14), and (16). The transformation results are presented in Table 5.

Where $\widetilde{E_m/Cr_n}$ represent the fuzzy number of E_m/Cr_n.

b) The calculation of the mean is performed to identify the fuzzy values of the weight coefficients for the evaluation criteria, $w = (w_1, w_2, w_3, \cdots\cdots, w_n)^T$. By summing the q-ROFS-EDM values from all experts, the final fuzzy weights for each criterion are computed. Formula (20) represents this process:

$$\widetilde{w_n} = \left(\sum_{m=1}^{m} \frac{\widetilde{E_m/Cr_n}}{\sum_{n=1}^{n} \widetilde{E_m \Big/ Cr_n}} \right) \Bigg/ m, n = 1, 2, 3, \ldots, n \tag{20}$$

c) Formula (18) is the defuzzification method to score each criterion. When computing the final values of the weight coefficients, the total weight of all criteria must sum up to 1. Otherwise, Formula (21) is employed to readjust the values:

$$w_i = w_i \Bigg/ \sum_{n=1}^{n} w_i, i = 1, 2, 3, \ldots, n \tag{21}$$

Where w_i represents the weight of each criterion.

The pseudocode of the q-ROFS–FWZIC weighting method is given below.

Algorithm 1: q-ROFS–FWZIC method	
Step 1: Define the power equipment supplier evaluation criteria:	
Identify $Cr[i]$	// *Cr* are the evaluation criteria.
Step **2:** SEJ:	
Define E $[i]$	//E is the array of experts appointed for evaluation.
Define DF, NS	//Define the data collection form (DF), and numerical scale (NS).
m = length (E)	
For each $i \in [1, E]$	//The DF of the power equipment supplier evaluation criteria is given to the experts who had previously agreed to participate.
If E $[i]$ is valid then E $[i] \leftarrow DF[i]$	
end if	
end for	
Step 3**:** Constructing EDM:	
Initialize E $DM[i,j]$	
n = length (Cr), m = length(E)	
For j $\in [1, n]$ For i $\in [1, m]$	//Map the expert's judgment about criterion Cr[j] using NS.
E $DM[i,j] = NS(E_{ij} / Cr_{ij})$	
end for	
end for	
Step 4: Application of q-ROFS Membership Function	
For j $\in [1, n]$ For i $\in [1, m]$	//Convert the EDM entries into fuzzy numbers to construct the fuzzy EDM ($\widetilde{EDM}$).
$\widetilde{EDM}[i,j] \leftarrow EDM[i,j]$	
end for	
end for	
Step 5: Calculate the final values of the assessment criteria weights.	
Step 5. a: compute the fuzzy data ratios	
For j $\in [1, n]$ For i $\in [1, m]$	//The ratio of fuzzification data is computed using Formulas (7), (14) and (16).
$\widetilde{E_i/Cr_j} = \frac{\widetilde{EDM}[i,j]}{\sum_{n=1}^{n} \widetilde{EDM}[i,j]}$	
end for	
end for	
Step 5. b: Aggregate the fuzzy values of the criteria:	
For j $\in [1, n]$	//The aggregation of the fuzzification data is calculated using Formula (20).
$\widetilde{w_j} = \left(\sum_{i=1}^{m} \frac{\widetilde{E_i/Cr_j}}{\sum_{j=1}^{n} \widetilde{E_i/Cr_j}} \right)$	
Step 5. c: Find the score values	
For j $\in [1, n]$	//Formula (18) is the defuzzification method and the final weight of each attribute is rescaled according to Formula (21).
$S(\widetilde{w_j}) = (1 + (\mu_Q(x))^2 - (\nu_Q(x))^2) / 2$	
end for	
If $\sum_{j=1}^{n} S(\widetilde{w_j}) \neq 1$	
then $w_j = w_j / \sum_{j=1}^{n} w_j$	
end if	

4.2.2. Q-ROFS-MABAC method

Given potential differences in decision-makers rankings of alternative solutions, it is essential to aggregate decisions from multiple evaluators to consolidate the rankings. Pamucar proposed the original MABAC method [32]. This study utilizes the fuzzy MABAC method, which is based on defining the distance between each alternative's standard function and the boundary approximation area. The specific steps are outlined as follows.

Step 1: Formation of the initial decision matrix, where the selected decision-making group of experts evaluates the alternative solutions based on criteria using the scale provided in Table 6, resulting in the opinion matrix P.

a . Personal Decision Making: According to the language terms and corresponding q-ROFS in Table 6, transform the opinion matrix P into a q-ROFS opinion matrix. Then, apply the score function equation (18) to defuse each alternative in order to obtain the initial decision matrix X.

$$X = \begin{array}{c} \\ A_1 \\ \cdots \\ A_m \end{array} \begin{array}{c} \begin{array}{ccc} C_1 & \dots & C_n \end{array} \\ \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \end{array} \tag{22}$$

Where m represents the number of alternative solutions, and n represents the total number of criteria.

b . Group Decision Making: Due to potential differences in how decision-makers rank alternatives, it is necessary to use group decision-making to reconcile these differences. Employ equation (16) for q-rung orthogonal fuzzy weighted arithmetic averaging (q-ROFA) aggregation operation to aggregate the opinion matrices from each expert. This process results in a new initial decision matrix.

Step 2: The elements in the initial decision matrix X are normalized, and the elements in the normalized matrix N are determined using the following formula:

$$n_{ij} = \frac{x_{ij} - x_i^-}{x_i^+ - x_i^-} \tag{23}$$

$$n_{ij} = \frac{x_{ij} - x_i^+}{x_i^- - x_i^+} \tag{24}$$

Formula (23) is used when higher values are preferable for the criteria, and formula (24) is used when lower values are preferable for the criteria. Where x_{ij}, x_i^-, x_i^+ represents the elements of the initial decision matrix X, x_i^+ is the maximum value observed for the criteria across alternatives, and x_i^- is the minimum value observed for the criteria across alternatives.

$$N = \begin{array}{c} 1 \\ \begin{bmatrix} n_{11} & \cdots & n_{1n} \\ \vdots & \ddots & \vdots \\ n_{m1} & \cdots & n_{mn} \end{bmatrix} \end{array} \tag{25}$$

Step 3: The elements of the weighted matrix (V) are computed using the weights (w) obtained from the q-ROFS-FWZIC method. This calculation is performed specifically by Formula (26).

$$v_{mn} = w_i \cdot (n_{mn} + 1) \tag{26}$$

Where n_{mn} is an element of the normalized matrix N, w_i is the weight coefficient of the criterion, and the resulting weighted matrix is as follows.

$$V = \begin{bmatrix} v_{11} & \cdots & v_{1n} \\ \vdots & \ddots & \vdots \\ v_{m1} & \cdots & v_{mn} \end{bmatrix} = \begin{bmatrix} w_1 \cdot (n_{11} + 1) & \cdots & w_n \cdot (n_{1n} + 1) \\ \vdots & \ddots & \vdots \\ w_1 \cdot (n_{m1} + 1) & \cdots & w_n \cdot (n_{mn} + 1) \end{bmatrix} \tag{27}$$

Step 4: Determine the border approximation area matrix (G). The border approximation area (BAA) for each criterion is determined according to Equation (28).

$$g_i = \left(\prod_{j=1}^{m} v_{ij} \right)^{\frac{1}{m}} \tag{28}$$

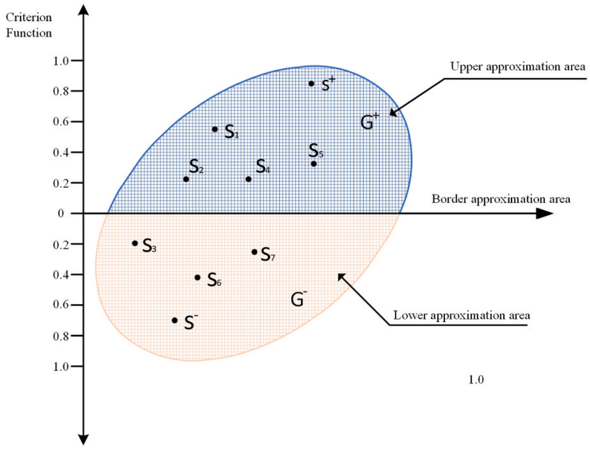

Fig. 4. Mabac region range.

Where v_{ij} is the element of the weighted matrix, and m is the total number of alternatives.

Step 5: Calculate the distance between each matrix cell of the alternatives and the boundary approximation area (Q).

$$Q = \begin{bmatrix} v_{11} - g_1 & \cdots & v_{1n} - g_n \\ \vdots & \ddots & \vdots \\ v_{m1} - g_1 & \cdots & v_{mn} - g_n \end{bmatrix} = \begin{bmatrix} q_{11} & \cdots & q_{1n} \\ \vdots & \ddots & \vdots \\ q_{m1} & \cdots & q_{mn} \end{bmatrix} \tag{29}$$

Alternative S^i could belong to the border approximation area (G), upper approximation area (G^+) or lower approximation area (G^-). The upper approximation area (G^+) is the area that contains the ideal alternative (s^+), while the lower approximation area (G^-) is the area which contains the anti-ideal alternative (s^-) as shown in Fig. 4 [32].

Step 6: Ranking of Alternatives. The final scores of the alternatives are calculated using Formula (30).

$$S_m = \sum_{n=1}^{n} q_{mn}, m = 1, 2, \ldots m \tag{30}$$

The pseudocode of the q-ROFS–MABAC weighting method is given below.

Algorithm 2: q-ROFS–MABAC method	
Step 1: Formation of the initial decision matrix:	
Define A $[i]$	// A are the suppliers.
Identify $Cr[i]$	Cr are the evaluation criteria.
for i $\in [1, \mathrm{m}]$ for j $\in [1, \mathrm{n}]$	//Where m represents the number of alternative solutions, and n represents the total number of criteria.
if Personal Decision Making (PDM)	E are the experts.
	Employ equation (16) q-ROFA aggregation operation to aggregate the opinion matrices from each expert.
$P[i,j] = \mathrm{PDM}(A_i / Cr_j)$	
else if Group Decision Making	
$P[i,j] = q - ROFA(\mathrm{PDM}[\mathrm{E}](A_i / Cr_j))$	
end if	
end for end for	
Step 2: normalize the initial decision matrix:	
for i $\in [1, \mathrm{m}]$ for j $\in [1, \mathrm{n}]$	//The elements in the initial decision matrix X are normalized, and the elements in the normalized matrix N are determined
N $[i,j] \leftarrow P[i,j]$	using formula (23), (24).
end for	
end for	
Step 3: Compute elements of the weighted matrix(V)	
Input Weights vector W	//W obtained from the q-ROFS-FWZIC
for i $\in [1, \mathrm{m}]$ for j $\in [1, \mathrm{n}]$	
$V[i,j] = w_j \cdot (N[i,j] + 1)$	
end for	
end for	
Step 4: Determine the border approximation area matrix (G)	
for j $\in [1, \mathrm{n}]$	//The border approximation area (BAA) for each criterion is determined according to Equation (28).

(*continued on next page*)

(*continued*)

Algorithm 2: q-ROFS–MABAC method	
$G[j] = \left(\prod_{i=1}^{m} V[i,j]\right)^{\frac{1}{m}}$	
end for	
Step 5: Calculate the distance	
for i ∈ [1, m] for j ∈ [1, n]	//Calculate the distance between each matrix cell of the alternatives and the boundary approximation area (Q).
$Q[i,j] = V[i,j] - G[j]$	
end for	
end for	
Step 6: Ranking of Alternatives.	
for i ∈ [1, m]	//The final scores of the alternatives are calculated using Formula (30).
$S[i] = \sum_{j=1}^{n} Q[i,j]$	
end for	

5. Case study

Transformers are devices that transfer electrical energy from one circuit to another, playing a crucial role in power networks. Due to their high cost and direct impact on power network operations, they are considered a fundamental component of the electrical grid. This section examines a case study evaluating power transformer equipment suppliers in Hubei Province, China, for the State Grid Corporation of China. Power transformers serve as critical hubs in power transmission, indispensable for the smooth operation of electrical systems. Evaluating and selecting suppliers for power transformers is more critical than for other equipment types. Evaluation criteria have been defined and identified in the problem statement, with a total of ten transformer suppliers participating in the assessment. The first part utilizes expert decisions to obtain standard weight coefficients and applies the q-ROFS-FWZIC method to derive actual weight coefficients. In the second part, the evaluation of suppliers is conducted using the mathematical framework of the q-ROFS-MABAC method.

5.1. *Weighting of criteria for power equipment suppliers*

This section introduces the final standard weights for evaluating power transformer suppliers, calculated using the q-ROFS-FWZIC method. In this approach, four experts provided assessment data for 10 criteria based on precise descriptions and the scale provided in Table 3. Subsequently, these linguistic expressions were converted into digital scales for constructing the EDM (see Appendix 1). In Step 4, the data was transformed into q-ROFS-EDM, as shown in Appendix 2. In Step 5a, the q-ROFS-EDM data was fuzzified using ratio transformation, with results detailed in Appendix 3. Then, as described in Step 5b, the average was computed to identify the expert fuzzy values for the assessment criteria weight coefficients. Following these steps, the decision matrices from the four participating experts were aggregated to obtain the final weight results, as presented in Table 7. In this study, the parameter q is set to 4 [62].

Failure Rate Per 100 Units (Cr4) is ranked as the most critical criterion, followed by Risk Priority Number (Cr6). Product Price (Cr8) and Financial Status (Cr3) are identified as the third and fourth important criteria. The remaining criteria, in descending order of importance, are Quality Sampling Qualification Rate (Cr5), Supply Performance (Cr2), Quality Fluctuation (Cr7), Enterprise Scale (Cr1), After-sale Service (Cr10), and CCIPP (Cr9). Under q values ranging from 4 to 10, changes in q lead to variations in the numerical weights assigned to each criterion, yet their relative importance remains unchanged. These final weights are integrated into the q-ROFS-MABAC method to effectively compute the evaluation results for power equipment suppliers.

5.2. *Ranking results of the suppliers*

In the first step of the q-ROFS-MABAC method, ten primary power transformer suppliers were selected. To assess and select these

Table 7
Criteria weighting results.

dimensions	criteria		Final Weights						
			q = 4	q = 5	q = 6	q = 7	q = 8	q = 9	q = 10
SR	Cr1	0.3047	0.0903	0.0903	0.0905	0.0909	0.0914	0.0920	0.0926
	Cr2	0.3465	0.1027	0.1025	0.1022	0.1019	0.1016	0.1013	0.1011
	Cr3	0.3488	0.1034	0.1031	0.1027	0.1023	0.1019	0.1016	0.1013
SQC	Cr4	0.2729	0.1159	0.1168	0.1172	0.1172	0.1169	0.1164	0.1156
	Cr5	0.2429	0.1031	0.1029	0.1025	0.1021	0.1018	0.1015	0.1012
	Cr6	0.2582	0.1096	0.1100	0.1101	0.1100	0.1097	0.1093	0.1089
	Cr7	0.2260	0.0960	0.0951	0.0944	0.0940	0.0939	0.0939	0.0940
PI	Cr8	1.0000	0.1040	0.1037	0.1033	0.1028	0.1023	0.1019	0.1016
SW	Cr9	0.4844	0.0847	0.0856	0.0868	0.0880	0.0891	0.0903	0.0913
	Cr10	0.5156	0.0902	0.0901	0.0903	0.0907	0.0913	0.0919	0.0925

suppliers, as outlined in Section 3, historical quality data for the ten suppliers were extracted, analyzed, and processed. Four experts evaluated the suppliers based on this historical quality data using the scale described in Table 6, and the evaluation language scale results are listed in Appendix 4. Individual decisions were initially made using Step 1. a method applied to Appendix 4, resulting in q-ROFS scale evaluation data for each expert. Fuzzy data was defuzzied using Formula 18 to obtain the initial decision matrix X, depicted in Appendix 5. The weighted normalized decision matrix N was calculated using Formulas (23) and (24), presented in Appendix 6. The boundary approximation region matrix G was determined by Formula 28, as outlined in Appendix 7. Based on the individual decision backgrounds of the four experts in power equipment suppliers using q-ROFS-MABAC, the final evaluation results are summarized in Table 8. Visualization of the results is illustrated in Fig. 5.

To obtain a consistent final ranking of power equipment suppliers, GDM is essential due to inherent variations. As outlined in Step 1 (B) of the q-ROFS-MABAC method, GDM aggregates the opinion matrices of individual experts using Formula 16, the q-ROFA aggregation operation. The supplier with the highest score is considered the best choice. The parameter q affects the weights of the criteria, leading to numerical changes in each weight as q varies, though it does not alter the relative importance of each criterion. To analyze the final rankings produced by q-ROFS-MABAC, Table 9 shows supplier rankings based on GDM q-ROFS-MABAC for q values of 1, 3, 5, 8, and 10, building on the individual q-ROFS-MABAC rankings presented in Table 8.

As shown in Table 9, for all values of q, the top supplier is A2, followed by A7. For q values of 1, 3, and 5, A6 ranks third, and A4 ranks fourth. However, with q set to 8, A4 moves up to third place while A6 drops to fourth. Finally, at $q = 10$, A3 ranks fourth. The parameter q plays a critical role in the overall ranking of suppliers in the q-ROFS-FWZIC-MABAC hybrid model and should be carefully considered. This analysis confirms that A2 emerges as the best supplier.

5.3. Ranking results under various dimensions

Utilize the evaluation results of this assessment model, comprehensive management of power engineering product suppliers is implemented. Fig. 6 illustrates the MABAC scores across various dimensions of suppliers. In this hybrid model, decision-makers can identify suppliers with poor quality. Supplier A10 exhibits the lowest SQC ranking, indicating lower quality levels and necessitating stronger quality control efforts for their power equipment to reduce operational risks in the power grid. Suppliers A8 and A9 show lower SR values, suggesting potential supply risks. It is crucial to monitor their production status closely to ensure timely delivery of equipment and actively seek alternative suppliers. The use of this research model provides a visual representation of the current performance of each supplier in terms of SR, SQC, PI, and SW, accompanied by practical recommendations. Furthermore, integrating with ESC enables dynamic updates of supplier assessments, facilitating ongoing management and control of suppliers.

5.4. Sensitivity analysis

To assess and demonstrate the robustness of the approach, sensitivity analysis was employed. In this evaluation process, the impact of changes in the weights of criteria on the supplier evaluation selection results was analyzed. In this study, Failure rate Per 100 Units (C4)emerged as the most important indicator across all q values among the 10 criteria used. The new weights were calculated using Equation (27) [63].

$$w_c = (1 - w_s) \times \left(\frac{w_c^o}{W_c^0}\right) = w_c^o - \Delta x \alpha_c \tag{27}$$

Where w_s is the most fundamental criterion, w_c^o is the weight calculated by q-ROFS-FWZIC, W_c^0 is the original sum of weights for changing criterion weight values, and Δx represents the range of variation applied to the weight values of 10 criteria, denoted as FPU (Cr4) in this study, as follows:

$$-0.1169 < \Delta x < 0.8831$$

The relative variation for each criterion relative to the most important criterion (Cr4) is calculated using the elasticity coefficient α_c

Table 8
Expert individual evaluation results.

Suppliers	Expert1		Expert2		Expert3		Expert4	
	Score	Ranks	Score	Ranks	Score	Ranks	Score	Ranks
A1	−0.059	7	−0.058	6	−0.071	7	−0.048	9
A2	0.289	2	0.285	1	0.270	1	0.197	2
A3	0.221	3	0.096	5	0.245	2	0.009	5
A4	0.049	6	0.220	4	0.132	5	0.134	4
A5	0.072	5	−0.095	8	−0.125	9	−0.023	8
A6	0.198	4	0.278	2	0.152	4	0.198	1
A7	0.290	1	0.232	3	0.153	3	0.152	3
A8	−0.120	8	−0.158	9	−0.124	8	−0.008	6
A9	−0.370	10	−0.340	10	−0.051	6	−0.228	10
A10	−0.227	9	−0.083	7	−0.189	10	−0.020	7

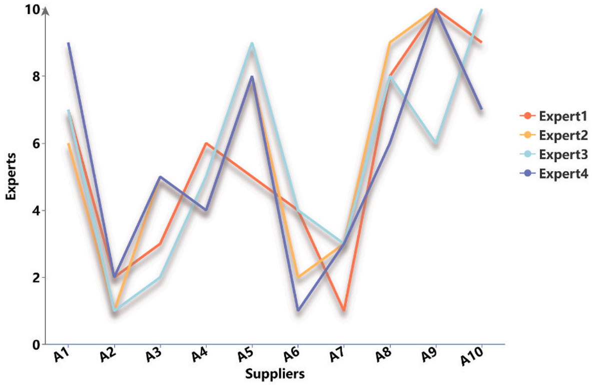

Fig. 5. Ranking results of four experts.

Table 9
GDM q-ROFS-MABAC ranking of the best suppliers.

q	Best four suppliers
q = 1	A2>A7>A6>A4
q = 3	A2>A7>A6>A4
q = 5	A2>A7>A6>A4
q = 8	A2>A7>A4>A6
q = 10	A2>A7>A4>A3

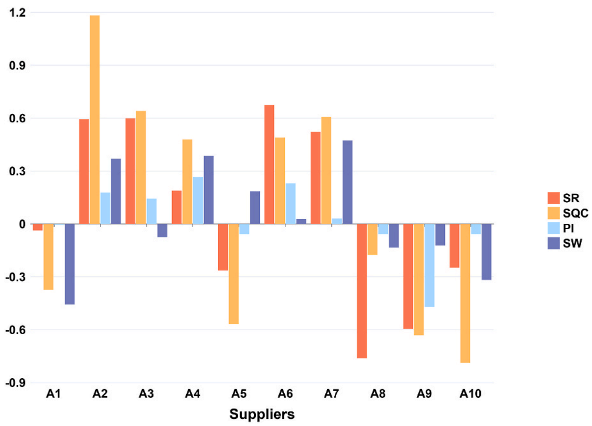

Fig. 6. Supplier scores for each dimension.

(q = 4), as shown in Table 10.

The range of Δx is divided into 9 equal parts, and 9 new weight values are generated for each criterion based on the interval range of Δx. This is depicted in Table 11.

When assessing the sensitivity of ranking results for 10 power transformer suppliers to changes in criterion weights, 9 new weight values were used. This analysis aimed to determine how q-ROFS-FWZIC weights affect the results. Fig. 7 presents the ranking results for power transformer suppliers across 9 scenarios. These results demonstrate the importance of criterion weights on the ranking of power transformer suppliers. In certain cases, altering criterion weights may affect the ranking of power transformer suppliers. In most scenarios, the proposed method exhibits significant robustness.

The new ranking results based on weights from the 9 scenarios need to be compared with the previous evaluation results obtained

Table 10
Elasticity coefficient.

	Cr1	Cr2	Cr3	Cr4	Cr5	Cr6	Cr7	Cr8	Cr9	Cr10
α_c	0.1022	0.1162	0.1170	0.1311	0.1167	0.1240	0.1086	0.1177	0.0958	0.1020

Table 11
New weights for 9 scenarios.

	Cr1	Cr2	Cr3	Cr4	Cr5	Cr6	Cr7	Cr8	Cr9	Cr10
q	0.0903	0.1027	0.1034	0.1159	0.1031	0.1096	0.0960	0.1040	0.0847	0.0902
S1	0.1022	0.1162	0.1170	0.0000	0.1167	0.1240	0.1086	0.1177	0.0958	0.1020
S2	0.0894	0.1016	0.1023	0.1250	0.1021	0.1085	0.0950	0.1030	0.0838	0.0893
S3	0.0766	0.0871	0.0877	0.2500	0.0875	0.0930	0.0814	0.0882	0.0719	0.0765
S4	0.0639	0.0726	0.0731	0.3750	0.0729	0.0775	0.0678	0.0735	0.0599	0.0638
S5	0.0511	0.0581	0.0585	0.5000	0.0583	0.0620	0.0543	0.0588	0.0479	0.0510
S6	0.0383	0.0436	0.0439	0.6250	0.0437	0.0465	0.0407	0.0441	0.0359	0.0383
S7	0.0255	0.0290	0.0292	0.7500	0.0292	0.0310	0.0271	0.0294	0.0240	0.0255
S8	0.0128	0.0145	0.0146	0.8750	0.0146	0.0155	0.0136	0.0147	0.0120	0.0128
S9	0.0000	0.0000	0.0000	1.0000	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

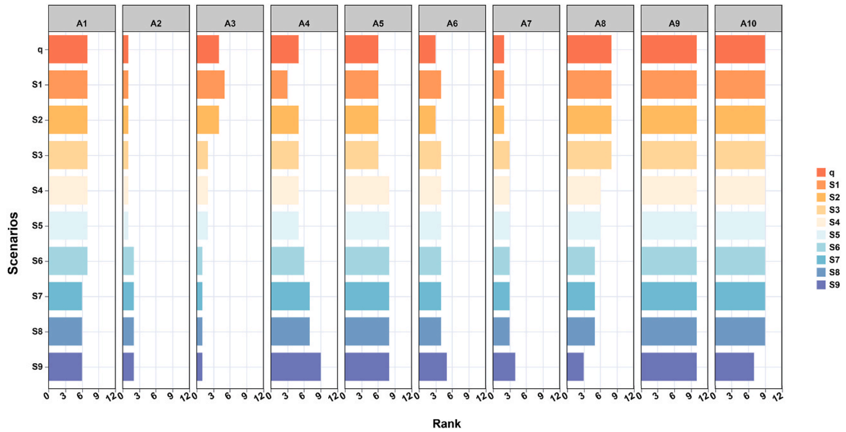

Fig. 7. Sensitivity analysis of power transformer supplier evaluation and selection.

using q-ROFS-FWZIC weights. According to the sensitivity analysis results visualized in Fig. 7, A2 ranked highest in scenarios S1-S5 but dropped to second place in scenarios S6-S9. A7 maintained second place in scenarios S1 and S2, dropped to third place in scenarios S3-S8, and further dropped to fourth place in scenario S9. A3 rose to second place in scenarios S3-S5 and claimed first place in scenarios S6-S10. A6 ranked second in scenario S2, fifth in scenario S9, and fourth in all other scenarios. A9 consistently held the lowest ranking across all scenarios, matching the original ranking results. The analysis highlights that the weights assigned to each evaluation criterion significantly influence the final ranking of power equipment suppliers. Lastly, the Spearman correlation coefficient (SCC) was used to statistically evaluate the relationships between results from different scenarios.

The correlation analysis in Fig. 8 reveals strong positive correlations among 8 scenarios and a positive correlation in one scenario. Specifically, scenario S2 exhibits the highest correlation with an SCC value of 0.9999, indicating a very strong relationship. In contrast,

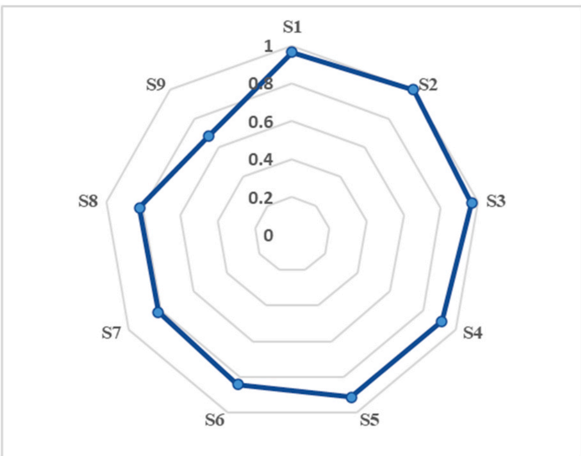

Fig. 8. Correlation analysis of supplier rankings across different scenarios.

scenario S9 shows the lowest SCC value of 0.6832. The remaining scenarios (S1, S3, S4, S5, S6, S7, S8) have SCC values ranging between these extremes: S1 and S3 with SCC values of 0.9636, S4 and S5 with SCC values of 0.9152, S6 with an SCC value of 0.8424, and S7 and S8 with SCC values of 0.8182. The average correlation coefficient across all scenarios is 0.8799, indicating consistently high correlation results. These findings support the ranking results obtained using the q-values, affirming their reliability across different evaluation scenarios.

6. Results and discussion

We have applied the proposed q-ROFS-FWZIC-MABAC hybrid model to evaluate power transformer suppliers. The evaluation of power transformer suppliers is recognized as an MCDM problem, and the analytical capabilities of this model address the issues within our research scope, which are novel in the literature.

Our study reveals the decision criteria that should be considered when evaluating suppliers providing equipment in the power sector. In the literature review section, various scholars have chosen criteria across different dimensions. To meet the safety requirements of the power grid operation, a new standard system has been constructed based on four dimensions. The results of the case application demonstrate that Failure rate Per 100 Units (Cr4) is the most critical criterion, while CCIPP (Cr9) is the least important. Analyzing the influence of parameter q on the final weight results, we found that increasing q values lead to corresponding changes in criterion weights but do not affect the final ranking of criteria.

The GDM supplier ranking shows that the top 4 suppliers are A2 > A7 > A6 > A4, with A2 being the optimal supplier. Comparing A2 with other suppliers reveals its superiority in the SQC dimension, which has the highest weighted ranking. This is a significant reason why A2 achieves the highest ranking. Supplier A7 scores higher than A6 in the SQC and SW dimensions but slightly lower in the SR and PI dimensions, which explains why A7 ranks higher than A6. Despite A4's overall performance being inferior to A6, its SW score is much higher than A6, indicating potential for greater future improvement, a merit that should not be entirely overlooked.

In this study, the robustness of the model was comprehensively tested and validated through sensitivity analysis and real case studies. Using formula 27, new weights were generated for 9 different scenarios. The stability and robustness of the method were validated using the Spearman correlation coefficient. The q-ROFS-FWZIC-MABAC hybrid method in the context of evaluating power equipment suppliers demonstrates its capability in data analysis and systematic comparison, contributing to methodological diversity in supplier evaluation.

Overall, to make informed final decisions, decision-makers must use appropriate methods that address the ambiguity and uncertainty in decision-making information, considering both the importance of evaluation criteria as determined by experts and the actual performance of various suppliers. The hybrid model introduced in this study offers an effective solution for evaluating power equipment suppliers.

7. Conclusion

The evaluation of power equipment suppliers is crucial for the security of the national power grid, especially given the current focus on energy security. With increasing energy demand and the development of renewable energy technologies, suppliers of power equipment face intensifying competition. Effective supplier evaluation directly impacts the operation of the power grid and the stability of the energy supply. Recognizing the growing importance of supplier quality in the power grid, the national grid company conducts regular assessments and monitors supplier performance.

This study proposes a novel decision model combining the FWZIC and MABAC methods within the q-ROFS environment to address the evaluation of power equipment suppliers, with quality performance as the core focus. Firstly, an evaluation framework for power equipment suppliers is constructed based on four dimensions: Supply Risk (SR), Supplier Quality Capability (SQC), Profit Impact (PI), and Supplier Willingness (SW), encompassing ten criteria. The FWZIC method within the fuzzy q-ROFS environment is then applied to calculate the weights of these criteria. Subsequently, the MABAC method is extended to the q-ROFS environment and combined with the aforementioned weights to rank alternative solutions. A case study on the evaluation and selection of power transformer suppliers is conducted to validate the model.

Sensitivity analysis demonstrates that the proposed approach can address uncertainties in the evaluation process while ensuring consistency in evaluation results. The significance of this research lies in assisting the National Grid company in regularly evaluating suppliers within its system. By dynamically adjusting management strategies based on evaluations across the four dimensions, the company can select suppliers with optimal quality to enhance the smooth and secure operation of the power grid. Additionally, it facilitates the timely identification of suppliers with poor quality performance, thereby strengthening quality control measures. This study provides decision support to the national grid company for assessing existing suppliers and prospects.

Despite these advantages, the current paper has three main limitations. Firstly, it does not consider variations in the technical expertise of experts. Addressing this issue could involve constructing expert weights based on their expertise levels. Secondly, only one defuzzification method and one fuzzy environment were used in both parts of the solution. Future research could consider expanding methods into other fuzzy environments. Thirdly, the q-ROFS-MABAC method used a single aggregation operator. Future studies may explore the use of alternative operators.

In conclusion, future research should focus on addressing these limitations and applying this integrated solution to broader issues in the power industry to promote its development and enhancement. This method can also be extended to other fields such as credit evaluation of manufacturing suppliers and evaluation and selection of distribution centers in the logistics sector, addressing various MCDM problems.

CRediT authorship contribution statement

Jiawei Mao: Writing – original draft, Validation, Investigation. **JinGuo Huang:** Writing – review & editing, Supervision, Methodology. **Jing Liu:** Validation, Supervision, Formal analysis, Conceptualization. **Chao Peng:** Writing – review & editing, Validation, Investigation. **ShiZe Zhang:** Methodology, Data curation, Conceptualization.

Data availability statement

The data that has been used is confidential.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix 1. EDM

Experts/ Criteria	Cr1	Cr2	Cr3	Cr4	Cr5	Cr6	Cr7	Cr8	Cr9	Cr10
E1	3	1	1	1	2	1	2	3	3	2
E2	2	2	2	1	1	2	1	2	1	1
E3	1	2	1	1	2	1	2	2	2	2
E4	2	1	2	1	1	1	2	2	3	3

Appendix 2. q-ROFs-EDM

Experts/ Criteria	Cr1	Cr2	Cr3	Cr4	Cr5	Cr6	Cr7	Cr8	Cr9	Cr10
E1	[0.55,0.55]	[0.95,0.15]	[0.95,0.15]	[0.95,0.15]	[0.75,0.35]	[0.95,0.15]	[0.75,0.35]	[0.95,0.15]	[0.55,0.55]	[0.75,0.35]
E2	[0.75,0.35]	[0.75,0.35]	[0.75,0.35]	[0.95,0.15]	[0.95,0.15]	[0.75,0.35]	[0.95,0.15]	[0.95,0.15]	[0.95,0.15]	[0.95,0.15]
E3	[0.95,0.15]	[0.75,0.35]	[0.95,0.15]	[0.95,0.15]	[0.75,0.35]	[0.95,0.15]	[0.75,0.35]	[0.75,0.35]	[0.75,0.35]	[0.75,0.35]
E4	[0.75,0.35]	[0.95,0.15]	[0.75,0.35]	[0.95,0.15]	[0.95,0.15]	[0.95,0.15]	[0.75,0.35]	[0.75,0.35]	[0.55,0.55]	[0.55,0.55]

Appendix 3. Ratio of q-ROFs-EDM

Experts/ Criteria	Cr1	Cr2	Cr3	Cr4	Cr5	Cr6	Cr7	Cr8	Cr9	Cr10
E1	[0.61,0.30]	[0.95,0.15]	[0.95,0.15]	[0.95,0.15]	[0.83,0.11]	[0.95,0.15]	[0.83,0.11]	[0.95,0.15]	[0.61,0.30]	[0.83,0.11]
E2	[0.82,0.12]	[0.82,0.12]	[0.82,0.12]	[0.95,0.15]	[0.95,0.15]	[0.82,0.12]	[0.95,0.15]	[0.95,0.15]	[0.95,0.15]	[0.95,0.15]
E3	[0.95,0.15]	[0.84,0.11]	[0.95,0.15]	[0.95,0.15]	[0.84,0.11]	[0.95,0.15]	[0.84,0.11]	[0.84,0.11]	[0.84,0.11]	[0.84,0.11]
E4	[0.85,0.10]	[0.95,0.15]	[0.85,0.10]	[0.95,0.15]	[0.95,0.15]	[0.95,0.15]	[0.85,0.10]	[0.85,0.10]	[0.63,0.30]	[0.63,0.30]

Appendix 4. Evaluation data in the MABAC model

Experts	Suppliers	Criteria									
		Cr1	Cr2	Cr3	Cr4	Cr5	Cr6	Cr7	Cr8	Cr9	Cr10
E1	A1	2	3	3	2	3	3	3	4	3	5
	A2	2	1	2	2	2	1	3	2	1	4
	A3	1	2	1	2	2	2	3	2	3	5
	A4	3	3	3	2	2	2	4	3	2	3
	A5	2	3	2	3	2	2	4	3	3	2
	A6	2	1	3	2	2	2	2	3	3	3
	A7	1	1	2	3	1	3	2	2	2	3
	A8	2	4	3	3	3	3	4	3	2	5
	A9	2	3	4	4	4	3	5	5	4	5
	A10	3	4	3	2	4	5	4	4	4	3
E2	A1	2	2	3	2	4	4	2	3	4	4
	A2	2	2	2	1	3	3	2	2	1	2
	A3	3	3	1	1	4	3	2	4	2	3
	A4	2	2	2	3	3	2	2	1	1	3
	A5	3	3	4	3	3	3	3	4	2	3
	A6	1	3	2	2	2	2	2	2	2	3
	A7	2	1	3	2	2	2	3	4	1	2
	A8	2	4	5	3	2	3	4	4	3	4
	A9	3	5	2	3	5	3	5	5	4	4
	A10	1	3	3	3	4	2	5	4	2	5
E3	A1	3	4	3	3	2	2	2	3	4	2
	A2	2	3	1	2	2	1	1	3	2	2
	A3	2	3	2	1	2	2	1	2	3	2
	A4	3	4	1	2	2	1	2	4	2	2
	A5	3	3	4	3	3	2	3	4	2	2
	A6	1	3	2	2	2	3	2	2	2	3
	A7	3	1	3	1	2	3	3	3	1	2
	A8	3	4	4	2	2	3	4	3	2	3
	A9	3	3	4	1	1	2	5	5	1	5
	A10	2	3	4	2	3	3	3	3	4	5
E4	A1	2	2	3	2	3	3	3	3	5	4
	A2	3	2	1	2	2	3	2	3	3	2
	A3	1	3	4	3	2	3	4	3	3	3
	A4	3	2	1	3	2	3	3	2	4	1
	A5	2	2	5	3	2	4	3	3	2	3
	A6	1	3	2	2	2	3	3	2	2	3
	A7	3	1	3	3	2	2	3	4	1	2
	A8	3	4	5	1	3	2	3	4	2	3
	A9	4	5	3	3	2	4	5	6	2	2
	A10	2	5	4	3	2	2	4	3	1	5

Appendix 5. Initial decision matrix X

Experts	Suppliers	Criteria									
		Cr1	Cr2	Cr3	Cr4	Cr5	Cr6	Cr7	Cr8	Cr9	Cr10
E1	A1	0.83	0.72	0.72	0.83	0.72	0.72	0.72	0.61	0.72	0.50
	A2	0.83	0.94	0.83	0.83	0.83	0.94	0.72	0.83	0.94	0.61
	A3	0.94	0.83	0.94	0.83	0.83	0.83	0.72	0.83	0.72	0.50
	A4	0.72	0.72	0.72	0.83	0.83	0.83	0.61	0.72	0.83	0.72
	A5	0.83	0.72	0.83	0.72	0.83	0.83	0.61	0.72	0.72	0.83
	A6	0.83	0.94	0.72	0.83	0.83	0.83	0.83	0.72	0.72	0.72
	A7	0.94	0.94	0.83	0.72	0.94	0.72	0.83	0.83	0.83	0.72
	A8	0.83	0.61	0.72	0.72	0.72	0.72	0.61	0.72	0.83	0.50
	A9	0.83	0.72	0.61	0.61	0.61	0.72	0.50	0.50	0.61	0.50
	A10	0.72	0.61	0.72	0.83	0.61	0.50	0.61	0.61	0.61	0.72
E2	A1	0.83	0.83	0.72	0.83	0.61	0.61	0.83	0.72	0.61	0.61
	A2	0.83	0.83	0.83	0.94	0.72	0.72	0.83	0.83	0.94	0.83
	A3	0.72	0.72	0.94	0.94	0.61	0.72	0.83	0.61	0.83	0.72
	A4	0.83	0.83	0.83	0.72	0.72	0.83	0.83	0.94	0.94	0.72
	A5	0.72	0.72	0.61	0.72	0.72	0.72	0.72	0.61	0.83	0.72
	A6	0.94	0.72	0.83	0.83	0.83	0.83	0.83	0.83	0.83	0.72
	A7	0.83	0.94	0.72	0.83	0.83	0.83	0.72	0.61	0.94	0.83
	A8	0.83	0.61	0.50	0.72	0.83	0.72	0.61	0.61	0.72	0.61

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Experts	Suppliers	Criteria									
		Cr1	Cr2	Cr3	Cr4	Cr5	Cr6	Cr7	Cr8	Cr9	Cr10
	A9	0.72	0.50	0.83	0.72	0.50	0.72	0.50	0.50	0.61	0.61
	A10	0.94	0.72	0.72	0.72	0.61	0.83	0.50	0.61	0.83	0.50
E3	A1	0.72	0.61	0.72	0.72	0.83	0.83	0.83	0.72	0.61	0.83
	A2	0.83	0.72	0.94	0.83	0.83	0.94	0.94	0.72	0.83	0.83
	A3	0.83	0.72	0.83	0.94	0.83	0.83	0.94	0.83	0.72	0.83
	A4	0.72	0.61	0.94	0.83	0.83	0.94	0.83	0.61	0.83	0.83
	A5	0.72	0.72	0.61	0.72	0.72	0.83	0.72	0.61	0.83	0.83
	A6	0.94	0.72	0.83	0.83	0.83	0.72	0.83	0.83	0.83	0.72
	A7	0.72	0.94	0.72	0.94	0.83	0.72	0.72	0.72	0.94	0.83
	A8	0.72	0.61	0.61	0.83	0.83	0.72	0.61	0.72	0.83	0.72
	A9	0.72	0.72	0.61	0.94	0.94	0.83	0.50	0.50	0.94	0.50
	A10	0.83	0.72	0.61	0.83	0.72	0.72	0.72	0.72	0.61	0.50
E4	A1	0.83	0.83	0.72	0.83	0.72	0.72	0.72	0.72	0.50	0.61
	A2	0.72	0.83	0.94	0.83	0.83	0.72	0.83	0.72	0.72	0.83
	A3	0.94	0.72	0.61	0.72	0.83	0.72	0.61	0.72	0.72	0.72
	A4	0.72	0.83	0.94	0.72	0.83	0.72	0.72	0.83	0.61	0.94
	A5	0.83	0.83	0.50	0.72	0.83	0.61	0.72	0.72	0.83	0.72
	A6	0.94	0.72	0.83	0.83	0.83	0.72	0.72	0.83	0.83	0.72
	A7	0.72	0.94	0.72	0.72	0.83	0.83	0.72	0.61	0.94	0.83
	A8	0.72	0.61	0.50	0.94	0.72	0.83	0.72	0.61	0.83	0.72
	A9	0.61	0.50	0.72	0.72	0.83	0.61	0.50	0.39	0.83	0.83
	A10	0.83	0.50	0.61	0.72	0.83	0.83	0.61	0.72	0.94	0.50

Appendix 6. Normalized matrix V

Experts	Suppliers	Criteria									
		Cr1	Cr2	Cr3	Cr4	Cr5	Cr6	Cr7	Cr8	Cr9	Cr10
E1	A1	0.136	0.137	0.138	0.232	0.138	0.164	0.160	0.139	0.113	0.090
	A2	0.136	0.205	0.172	0.232	0.172	0.219	0.160	0.208	0.169	0.120
	A3	0.181	0.171	0.207	0.232	0.172	0.192	0.160	0.208	0.113	0.090
	A4	0.090	0.137	0.138	0.232	0.172	0.192	0.128	0.173	0.141	0.150
	A5	0.136	0.137	0.172	0.174	0.172	0.192	0.128	0.173	0.113	0.180
	A6	0.136	0.205	0.138	0.232	0.172	0.192	0.192	0.173	0.113	0.150
	A7	0.181	0.205	0.172	0.174	0.206	0.164	0.192	0.208	0.141	0.150
	A8	0.136	0.103	0.138	0.174	0.138	0.164	0.128	0.173	0.141	0.090
	A9	0.136	0.137	0.103	0.116	0.103	0.164	0.096	0.104	0.085	0.090
	A10	0.090	0.103	0.138	0.232	0.103	0.110	0.128	0.139	0.085	0.150
E2	A1	0.136	0.180	0.155	0.174	0.138	0.110	0.192	0.156	0.085	0.120
	A2	0.136	0.180	0.181	0.232	0.172	0.164	0.192	0.182	0.169	0.180
	A3	0.090	0.154	0.207	0.232	0.138	0.164	0.192	0.130	0.141	0.150
	A4	0.136	0.180	0.181	0.116	0.172	0.219	0.192	0.208	0.169	0.150
	A5	0.090	0.154	0.129	0.116	0.172	0.164	0.160	0.130	0.141	0.150
	A6	0.181	0.154	0.181	0.174	0.206	0.219	0.192	0.182	0.141	0.150
	A7	0.136	0.205	0.155	0.174	0.206	0.219	0.160	0.130	0.169	0.180
	A8	0.136	0.128	0.103	0.116	0.206	0.164	0.128	0.130	0.113	0.120
	A9	0.090	0.103	0.181	0.116	0.103	0.164	0.096	0.104	0.085	0.120
	A10	0.181	0.154	0.155	0.116	0.138	0.219	0.096	0.130	0.141	0.090
E3	A1	0.090	0.103	0.138	0.116	0.155	0.164	0.168	0.173	0.085	0.180
	A2	0.136	0.137	0.207	0.174	0.155	0.219	0.192	0.173	0.141	0.180
	A3	0.136	0.137	0.172	0.232	0.155	0.164	0.192	0.208	0.113	0.180
	A4	0.090	0.103	0.207	0.174	0.155	0.219	0.168	0.139	0.141	0.180
	A5	0.090	0.137	0.103	0.116	0.103	0.164	0.144	0.139	0.141	0.180
	A6	0.181	0.137	0.172	0.174	0.155	0.110	0.168	0.208	0.141	0.150
	A7	0.090	0.205	0.138	0.232	0.155	0.110	0.144	0.173	0.169	0.180
	A8	0.090	0.103	0.103	0.174	0.155	0.110	0.120	0.173	0.141	0.150
	A9	0.090	0.137	0.103	0.232	0.206	0.164	0.096	0.104	0.169	0.090
	A10	0.136	0.137	0.103	0.174	0.103	0.110	0.144	0.173	0.085	0.090
E4	A1	0.151	0.180	0.155	0.174	0.103	0.164	0.160	0.182	0.085	0.113
	A2	0.120	0.180	0.207	0.174	0.206	0.164	0.192	0.182	0.127	0.158
	A3	0.181	0.154	0.129	0.116	0.206	0.164	0.128	0.182	0.127	0.135
	A4	0.120	0.180	0.207	0.116	0.206	0.164	0.160	0.208	0.106	0.180
	A5	0.151	0.180	0.103	0.116	0.206	0.110	0.160	0.182	0.148	0.135
	A6	0.181	0.154	0.181	0.174	0.206	0.164	0.160	0.208	0.148	0.135
	A7	0.120	0.205	0.155	0.116	0.206	0.219	0.160	0.156	0.169	0.158

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Experts	Suppliers	Criteria									
		Cr1	Cr2	Cr3	Cr4	Cr5	Cr6	Cr7	Cr8	Cr9	Cr10
	A8	0.120	0.128	0.103	0.232	0.103	0.219	0.160	0.156	0.148	0.135
	A9	0.090	0.103	0.155	0.116	0.206	0.110	0.096	0.104	0.148	0.158
	A10	0.151	0.103	0.129	0.116	0.206	0.219	0.128	0.182	0.169	0.090

Appendix 7. Border approximation area G

Experts	Criteria									
	Cr1	Cr2	Cr3	Cr4	Cr5	Cr6	Cr7	Cr8	Cr9	Cr10
E1	0.1323	0.1493	0.1492	0.1983	0.1512	0.1729	0.1442	0.1664	0.1187	0.1220
E2	0.1271	0.1566	0.1601	0.1503	0.1613	0.1772	0.1547	0.1452	0.1317	0.1385
E3	0.1093	0.1308	0.1394	0.1747	0.1468	0.1481	0.1506	0.1634	0.1293	0.1514
E4	0.1357	0.1527	0.1483	0.1402	0.1796	0.1653	0.1480	0.1714	0.1350	0.1375

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