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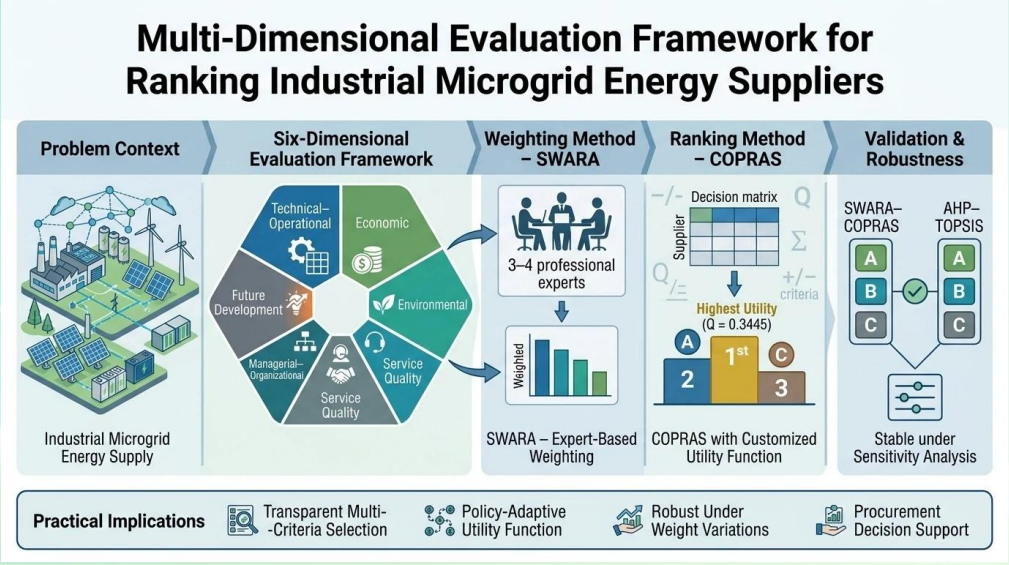
Developing a Multi-Dimensional Evaluation Framework for Ranking Applicants Participating in Industrial Microgrid Energy Supply Projects

Mohammad Gholami, Masume Khodsuz

Highlights

- **A hybrid SWARA–COPRAS framework is proposed for evaluating and ranking energy suppliers in industrial microgrids.**
- **A comprehensive set of criteria was developed, covering technical-operational, economic, environmental, managerial, service, and future development aspects.**
- **The framework was validated through a case study in which Supplier A achieved the highest utility score and remained top-ranked under different weighting scenarios.**
- **Comparative analysis with AHP–TOPSIS confirmed the robustness, transparency, and reliability of the proposed decision-support approach.**

Graphical Abstract



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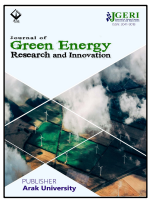
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Developing a Multi-Dimensional Evaluation Framework for Ranking Applicants Participating in Industrial Microgrid Energy Supply Projects

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A B S T R A C T

With the growing need for sustainable and optimized energy supply in industrial areas, microgrids have emerged as an effective solution. Accordingly, selecting capable companies to provide energy through industrial microgrids requires a structured evaluation and ranking process. This paper presents a hybrid decision-making framework that integrates Step-wise Weight Assessment Ratio Analysis (SWARA) and Complex Proportional Assessment (COPRAS) to assess and rank energy supply applicants. Key criteria and sub-criteria, including technical-operational, economic, environmental, managerial, service-oriented, and future development aspects, were identified and weighted based on expert judgment. A customized utility formulation was applied within the COPRAS method to accommodate domain-specific priorities. A case study involving three candidate companies demonstrated the practical application of the framework: Supplier A achieved the highest utility score (Q = 0.3445) and consistently ranked first across multiple weighting scenarios. Comparative analysis with AHP + TOPSIS confirmed the reliability of the results. The proposed framework offers transparency, adaptability, and robustness, making it a valuable decision-support tool for industrial energy procurement.

1. Introduction

The increasing global energy demand and the environmental consequences of fossil fuel consumption have highlighted the urgent need for sustainable and intelligent energy systems [1]. Industrial towns, as major production and employment hubs, represent a significant share of national energy consumption. Their reliance on the centralized power grid, combined with fluctuations in supply, can adversely affect productivity, competitiveness, and sustainable industrial development [2]. Smart industrial microgrids have emerged as a promising solution [3–5], offering localized energy systems capable of operating independently or in coordination with the main grid, thereby ensuring reliable and resilient energy supply [6]. By integrating renewable energy sources, energy storage, and advanced management technologies, these microgrids enhance energy sustainability, flexibility, and security [7].

The effectiveness of industrial microgrids largely depends on the active participation of private sector energy suppliers. Therefore, establishing a robust and transparent framework for evaluating and ranking potential suppliers is essential [8]. Such a framework enables the selection of providers that balance service quality, cost-effectiveness, and environmental responsibility, while supporting continuous improvement and long-term sustainability [6]. Recent studies often employ multi-criteria decision-making (MCDM) methods in the energy sector to assess technologies, projects, or supply scenarios, typically focusing on technical, economic, and environmental indicators. For instance, for example, in [9], a fuzzy MCDM framework was developed to rank renewable energy projects under uncertainty. In [10], a hybrid MCDM model was proposed to select the most sustainable power-generating technology, incorporating economic, environmental, social, and technical dimensions. In [11], the Analytic Hierarchy Process (AHP) was applied to rank alternative energy supply scenarios for a local microgrid, combining sustainability criteria with cost and reliability considerations.

Other works, such as [12], have reviewed MCDM applications in sustainable renewable energy development, highlighting the frequent use of AHP, TOPSIS (Technique for Order Preference by Similarity to Ideal Solution), VIKOR (VIseKriterijumska Optimizacija I Kompromisno Resenje), and COPRAS (Complex Proportional Assessment) in energy-related contexts. In [13], a COPRAS-based framework was used to assess renewable electricity generation technologies, illustrating its capability to handle multiple conflicting criteria. In [14], an integrated AHP–TOPSIS approach was applied to renewable energy supplier selection for industrial settings, focusing on cost, reliability, renewable share, and emissions. In [15], a VIKOR-based method was employed to evaluate renewable energy producers, prioritizing technical stability and grid integration, while [16] applied the Analytic Network Process (ANP) to account for interdependencies among evaluation criteria in microgrid supplier selection. Despite these contributions, existing studies primarily focus on evaluating technologies, projects, or energy mix scenarios rather than directly assessing private energy suppliers in industrial microgrids. Moreover, most frameworks consider only three or four dimensions, typically technical, economic, and environmental, while neglecting service quality, managerial capacity, and development potential.

To address these gaps, we propose a comprehensive six-dimensional evaluation framework, technical-operational, economic, environmental, service quality, managerial-organizational, and future development potential, weighted using the SWARA (Step-wise Weight Assessment Ratio Analysis) method and ranked via COPRAS. The framework is applied to a hypothetical case study, as obtaining such detailed data from real energy suppliers was not feasible. The key contributions of this paper are as follows:

- Development of a comprehensive set of performance indicators for assessing energy suppliers in industrial microgrids, covering economic, technical-operational, environmental, service, managerial, and developmental dimensions.
- Introduction of a novel supplier evaluation and ranking framework utilizing MCDM methods to ensure balanced and robust decision-making.

The remainder of the paper is structured as follows: Section 2 discusses the conceptual foundation of the proposed framework, including evaluation criteria and relevant MCDM methods. Section 3 presents the proposed methodology for evaluating and ranking energy suppliers. Section 4 illustrates the application of the framework in a practical case study, followed by discussion and analysis of the results.

2. Fundamental Principles

As previously discussed, the ranking framework for private energy suppliers is a critical decision-support tool for evaluating and optimally selecting companies for energy supply projects, particularly in industrial settings. The process begins by defining key evaluation criteria and assigning appropriate weights based on project-specific priorities. The output of this framework is a comprehensive evaluation report that highlights each company's strengths and weaknesses, thereby enabling decision-makers to select the most suitable provider by balancing cost-efficiency, sustainability, and performance. This structured and transparent approach not only mitigates risks but also supports the development of green energy infrastructure in industrial zones. In this context, the next sub-section presents a set of key performance indicators designed to assess the capabilities of companies applying to provide energy supply services for industrial microgrids. These indicators ensure a comprehensive evaluation across multiple critical dimensions.

2.1. Ranking Indicators

A central innovation of this study is the development of a comprehensive and multidimensional evaluation framework for ranking private energy suppliers in industrial microgrids. Unlike previous studies that focus narrowly on technical or financial metrics, this framework integrates six critical dimensions, technical–operational, economic, environmental, service, managerial–organizational, and future development, each with carefully selected sub-indicators. This holistic structure enables decision-makers to assess suppliers not only on performance and cost, but also on sustainability, reliability, customer orientation, and long-term adaptability [1,12,14].

2.1.1. Technical and Operational Indicators

These indicators assess the supplier's capability to design, implement, and operate a robust microgrid. In the pre operational stage, technical design quality and system reliability are often weighted higher than other indicators as literature shows early design flaws have longer term performance and cost implications [4-5,8,17]. Key indicators:

- Technical Design Quality: Assesses the completeness, innovation, and standard compliance of the proposed design, including system architecture, equipment specs, and risk mitigation strategies.
- System Reliability: Measures the supplier's ability to ensure uninterrupted energy delivery through redundancy, backup systems, and adaptability to load fluctuations.
- Equipment Efficiency: Evaluates the nominal energy conversion efficiency of proposed equipment, serving as a proxy for performance in the absence of operational data.
- Power Quality: Assesses voltage and frequency stability, harmonic distortion control, and reactive power management, which directly affect system performance and user satisfaction.
- Energy Supply Sustainability: Combines total supply capacity with the share of renewable energy sources, reflecting both reliability and environmental responsibility.
- System Safety: Reviews safety protocols, compliance with OSHA/IEC standards, and workforce training programs to minimize operational risks.

2.1.2. Economic Indicators

Economic strength ensures that a supplier can not only start but sustain a project. Literature emphasizes financial robustness and realistic cost planning as predictors of project continuity [2,11,13].

- Financial Capability: Reflects the company's overall financial health, ability to secure capital, and long-term economic stability.
- Proposed Financial Resources: Evaluates the diversity and reliability of funding sources, including internal capital, loans, and external investors.
- Financing Plans: Assesses the clarity and feasibility of capital acquisition strategies and repayment schedules based on projected cash flows.
- Projected Costs: Reviews detailed estimates of investment, operational, and maintenance costs to ensure realistic financial planning.
- Predicted IRR: Indicates the expected return on investment, helping assess the financial attractiveness and viability of the project.

2.1.3. Environmental Indicators

Environmental performance is central to sustainable industrial development [6,14,18-19]. Emission based metrics provide a transparent, comparable basis for evaluation. Key indicators:

- Environmental Commitments & Standards: Assesses compliance with environmental regulations and voluntary sustainability initiatives beyond legal requirements.
- CO_2 Intensity: Measures carbon emissions per megawatt-hour (g/MWh), based on the proposed energy mix and technology portfolio.
- NOx, SOx, CO Intensity: Evaluates emissions of harmful gases that affect air quality and public health, calculated relative to energy output.
- PM Emission Intensity: Assesses the release of fine particulate matter from combustion processes, which contributes to smog and respiratory issues.

2.1.4. Service Criteria & Commitments

These indicators reflect the supplier's ability to deliver reliable service and maintain customer satisfaction [13].

- Service Quality: Evaluates the supplier's plans for technical support, maintenance scheduling, and responsiveness to customer needs.
- Contractual Commitments: Reviews the transparency, comprehensiveness, and enforceability of proposed service contracts and guarantees.
- Customer Satisfaction Programs: Assesses mechanisms for collecting feedback, conducting surveys, and implementing service improvements.

2.1.5. Managerial & Organizational Criteria

These indicators evaluate the supplier's internal capacity to manage complex energy projects [3,13].

- Execution Team: Assesses the experience, expertise, and leadership capabilities of the project team, especially in similar energy projects.
- Risk Management: Evaluates the presence of proactive strategies to identify, assess, and mitigate technical, financial, and operational risks.
- Monitoring & Evaluation: Reviews tools and processes for tracking project progress, reporting performance, and enabling continuous improvement.

2.1.6. Future Development & Network Flexibility

These indicators assess the supplier's readiness for future growth and adaptability [13,15].

- Capacity Expansion & Demand Forecasting: Evaluates the supplier's ability to scale energy production and anticipate future demand trends.
- Network Flexibility: Assesses the system's ability to adapt to fluctuations in renewable energy generation and respond to disruptions.
- Use of Advanced Technologies: Reviews the integration of AI, IoT, and smart energy management systems for optimization and control.
- Risk Reduction Plans: Evaluates preparedness for unforeseen events through contingency planning and adaptive infrastructure.

2.2. Overview of MCDM Methods:

Multi-Criteria Decision-Making (MCDM) methods provide structured tools for evaluating multiple alternatives based on diverse and often conflicting criteria. These techniques are widely applied in engineering, economics, and management, and are particularly effective in complex decision environments such as energy supplier selection for industrial microgrids [20].

MCDM enables decision-makers to identify relevant criteria, assign weights, and rank alternatives based on performance, offering rational trade-offs and transparent prioritization.

2.2.1. Classical MCDM Techniques

Several well-established MCDM methods have been developed over the past decades:

- AHP: Introduced by Saaty [21], AHP uses pairwise comparisons and a hierarchical structure to derive criteria weights and rank alternatives. It includes a consistency check but becomes computationally intensive with many criteria.
- ANP: A generalization of AHP that models interdependencies among criteria and alternatives [22]. Suitable for non-hierarchical decision systems.
- TOPSIS: Developed by Hwang and Yoon [23], this method ranks alternatives based on their distance from ideal and anti-ideal solutions. It is intuitive but sensitive to normalization.
- VIKOR: Proposed by Opricovic and Tzeng [24], VIKOR identifies compromise solutions by balancing individual and group utility.
- ELECTRE (ELimination Et Choix Traduisant la REalité) & PROMETHEE (Preference Ranking Organization Method for Enrichment Evaluations): Outranking methods that handle qualitative and uncertain data. ELECTRE [25] uses concordance and discordance indices, while PROMETHEE [26] relies on preference flows.
- BWM (Best Worst Method): Introduced by Rezaei [27], BWM reduces the number of comparisons by focusing on the best and worst criteria, offering higher consistency and stability.

2.2.2. SWARA + COPRAS Hybrid Approach

To address the limitations of classical methods and enhance decision-making efficiency, this study adopts a hybrid approach combining SWARA for criteria weighting and COPRAS for alternative ranking. This combination is recognized for its simplicity, transparency, and adaptability in expert-driven environments [28,29]. Advantages of this hybrid method, include:

- Low computational burden: Unlike ANP, SWARA and COPRAS use straightforward calculations.
- No exhaustive pairwise comparisons: SWARA uses sequential expert judgment, reducing inconsistency.
- Handles both beneficial and non-beneficial criteria: COPRAS directly incorporates cost-type criteria.
- Suitable for expert and group decisions: SWARA performs well even with limited expert input.
- Easy implementation: Can be executed in Excel without specialized software.
- Adaptable to fuzzy/grey systems: Extensions exist for uncertain environments.
- Supports rapid decisions: Ideal for time-sensitive industrial applications.

Comparative Advantages of SWARA + COPRAS over Other MCDM Methods has been shown in Table 1.

2.2.3. SWARA Method Steps

SWARA is a judgment-based method for deriving criteria weights [28].

Identify criteria: List relevant decision criteria.

Rank criteria: Experts rank criteria by importance.

Calculate relative importance (sj): sj = Relative importance of criterion j compared to criterion $j-1$

Calculate recalculated coefficient (kj) using Equation (1):

$$k_j = \begin{cases} 1 & if\ j = 1 \\ s_j + 1 & if\ j > 1 \end{cases} \tag{1}$$

Calculate initial weight (qj) using Equation (2):

$$q_j = \begin{cases} 1 & if\ j = 1 \\ \dfrac{q_{j-1}}{k_j} & if\ j > 1 \end{cases} \tag{2}$$

Calculate final weight (wj) using Equation (3):

$$w_j = \frac{q_j}{\sum_{j=1}^{n} q_j} \tag{3}$$

Table 1. Comparative Advantages of SWARA + COPRAS over Other MCDM Methods.

Comparison Criterion	SWARA + COPRAS	AHP	TOPSIS	VIKOR
Computational Load	Low	Medium to High	Low	Medium
Sensitivity to Subjectivity	Low	High	Moderate	High
Implementation Simplicity	Very Easy	Moderate	Easy	Moderate
Support for Negative Criteria	Yes (COPRAS)	Through Conversion	Through Conversion	Yes
Real-World Applicability	High	Limited	Good	Good

2.2.4. COPRAS Method Steps

COPRAS ranks alternatives based on both beneficial and non-beneficial criteria [29].

Form decision matrix ($x = \left[x_{ij} \right]$): Alternatives (rows) × criteria (columns).

Normalize matrix ($r = \left[r_{ij} \right]$), as given in Equation (4):

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \tag{4}$$

Form weighted matrix ($v = \left[v_{ij} \right]$) using Equation (5):

$$v_{ij} = r_{ij}.w_j \tag{5}$$

Calculate profit (S_i^+) and cost (S_i^-) values based on Equations (6) and (7):

$$S_i^+ = \sum_{j \in J^+} v_{ij} \tag{6}$$

$$S_i^- = \sum_{j \in J^-} v_{ij} \tag{7}$$

Calculate relative index (Qi) according to Equation (8):

$$Q_i = \frac{\sum_{i=1}^{m} S_i^-}{S_i^- \sum_{i=1}^{m} \frac{1}{S_i^-}} + S_i^+ \tag{8}$$

Calculate final evaluation degree (Ui) as given in Equation (9):

$$U_i = \frac{Q_i}{\max\limits_{j \in [1,m]} (Q_j)} \times 100 \tag{9}$$

Rank alternatives: Based on descending values of Ui.

3. Proposed Evaluation Framework and Ranking Process

The evaluation of energy suppliers for industrial microgrids demands a structured, multidimensional framework that reflects the technical, economic, environmental, service-related, managerial, and developmental aspects of each applicant. As illustrated in Figure 1, the framework is built upon six main categories of indicators, each comprising several sub-indicators selected for their relevance to early-stage decision-making. These indicators serve as the foundation for the weighting and scoring process, which ultimately guides the ranking and selection of optimal suppliers. Following the identification of indicators, the evaluation process proceeds through three key stages: weighting, scoring, and ranking. Weighting determines the relative importance of each indicator and sub-indicator, scoring assesses the performance of applicants against these criteria, and ranking integrates both steps using a hybrid MCDM approach.

3.1. Weighting of Indicators and Sub-indicators

Assigning appropriate weights is essential to ensure that the evaluation framework aligns with the strategic priorities of industrial parks. Expert input is gathered from professionals in energy systems, industrial operations, and strategic management to reflect real-world conditions and contextual needs. The weighting process is conducted in two stages: first for the six main indicators, and then for the sub-indicators within each category.

3.1.1. Main Indicators

Table 2 presents the six primary evaluation indicators alongside expert-assigned weights. Each expert assigns a score between 0 and 10 based on perceived importance. The table reflects input from three experts and can be updated to accommodate additional feedback or changing priorities.

Table 2. Weighting of primary indicators based on expert opinions.

Main Indicators	Assigned Weights		
	Expert 1	Expert 2	Expert 3
Technical & Operational			
Economic			
Environmental			
Service & Customer Commitments			
Managerial & Organizational			
Future Development & Flexibility			

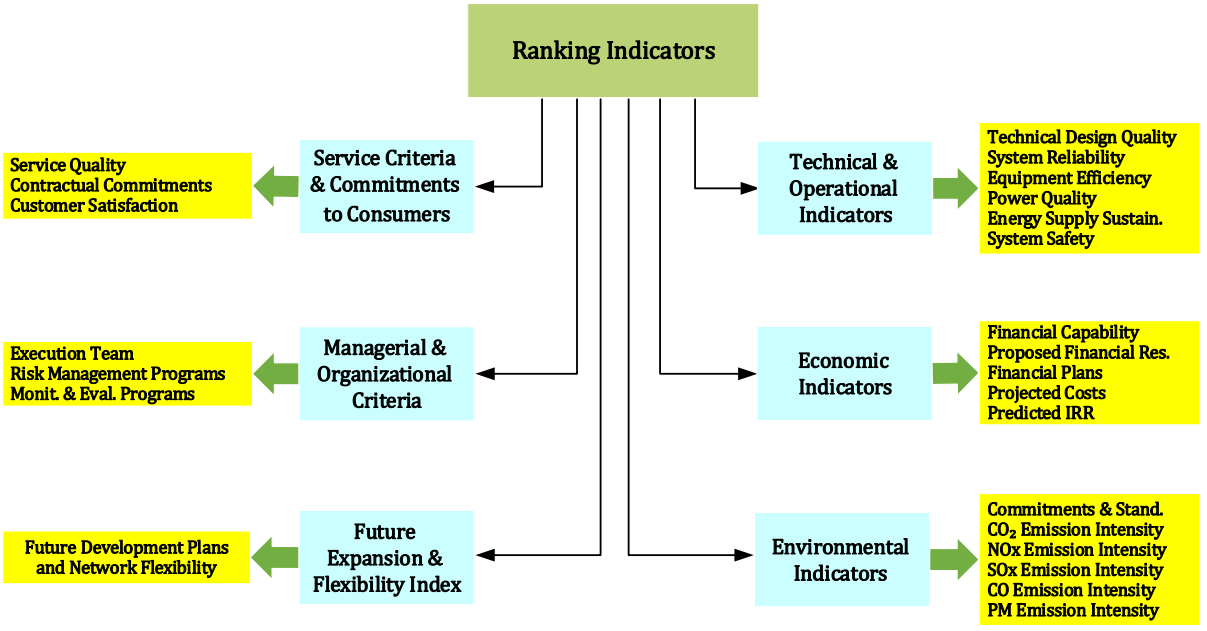


Figure 1. Primary and secondary indicators for evaluating energy supply applicants.

The rationale for weighting is supported by prior studies:

Technical & Operational indicators receive the highest weight due to their direct impact on system reliability, energy quality, and equipment performance [4,5,17]. Studies show that technical robustness is a key determinant of microgrid success, regardless of financial or managerial capacity. Economic indicators follow, reflecting the importance of financial capacity in infrastructure development and long-term viability [13,26]. Access to capital and sound financial planning are consistently linked to project feasibility and scalability. Environmental indicators are prioritized for their role in regulatory compliance and sustainability [6], [10,18]. Emission control and renewable integration are increasingly critical under tightening climate policies. Service & Customer Commitments are essential for operational continuity and user satisfaction [10,29]. Poor service delivery can undermine even technically sound systems. Managerial & Organizational indicators contribute to strategic execution but are secondary to technical and financial factors [3,27].Future Development & Flexibility is weighted lowest in initial evaluations but remains relevant for long-term success [15,28].

3.1.2. Sub-indicators

Similar to the main indicators, sub-indicators are weighted based on expert judgment. As shown in Table 3, each group of sub-indicators is accompanied by a weighting column to be completed by experts. The scores reflect the perceived significance of each sub-indicator in evaluating applicants for energy supply to industrial microgrids.

The prioritization of sub-indicators is based on their operational impact, contribution to risk mitigation, and strategic relevance:

System Reliability and Supply Sustainability are weighted highest due to their role in uninterrupted energy delivery [5,17].

Financial Capability and Financing Plans are emphasized for their influence on project execution [13,26].

CO_2 and NO_x/SO_x emissions are prioritized for their regulatory and health implications [6,18,19].

Service Quality and Contractual Commitments are key to customer retention and operational trust [10,29].

Leadership and Risk Management are valued for strategic resilience [3,27].

Network Flexibility and Future Planning support long-term adaptability [15,28].

This structured weighting ensures that operationally and strategically impactful sub-indicators are prioritized, resulting in a transparent and goal-oriented evaluation framework.

Table 3. Weighting of the sub-indicators based on expert opinions.

Sub Indicators	Assigned Weights		
	Expert 1	Expert 2	Expert 3
Sub-indicator 1			
Sub-indicator 2			
Sub-indicator 3			
Sub-indicator 4			
⋮			

3.2. Evaluation and Ranking of Applicants

The final stage involves evaluating and ranking applicant companies based on the weighted indicators. This process directly influences operational costs, energy supply reliability, service quality, and environmental impact. To ensure objectivity, both quantitative and qualitative data are collected and normalized to a common scale (e.g., 0–10). Table 4 presents the evaluation scores of sub-indicators for each applicant, based on expert review of documentation, reports, interviews, and site visits.

To rank the applicants, a hybrid MCDM method is applied:

SWARA is used to derive the final weights of indicators based on expert input.

COPRAS ranks the applicants by evaluating both beneficial and non-beneficial criteria using those weights.

This integrated approach enables balanced, transparent, and strategic selection. It supports cost optimization, enhances reliability, and contributes to the long-term sustainability of energy supply in industrial parks.

The overall process is illustrated in Figure 2, which presents a flowchart from indicator identification and weighting to final evaluation and selection.

Table 4. Evaluation of the sub-indicators of applicant companies based on expert opinions.

Main Indicators	Sub-Indicators	Scores		
		Expert 1	Expert 2	Expert 3
Technical & Operational	Technical Design Quality			
	System Reliability			
	Equipment Efficiency			
	Power Quality			
	Energy Supply Sustainability			
	System Safety			
Economic	Financial Capability			
	Proposed Financial Resources			
	Financing Plans			
	Projected Costs			
	Predicted IRR			
Environmental	Environmental Commitments and Standards			
	CO_2 Emission Intensity			
	NO_x Emission Intensity			
	SO_x Emission Intensity			
	CO Emission Intensity			
	PM Emission Intensity			
Service & Customer Commitments	Service Quality			
	Contractual Commitments			
	Customer Satisfaction			
Managerial & Organizational	Execution Team			
	Risk Management Programs			
	Monitoring and Evaluation Programs			
Future Development & Flexibility	Future Development Plans and Network Flexibility			

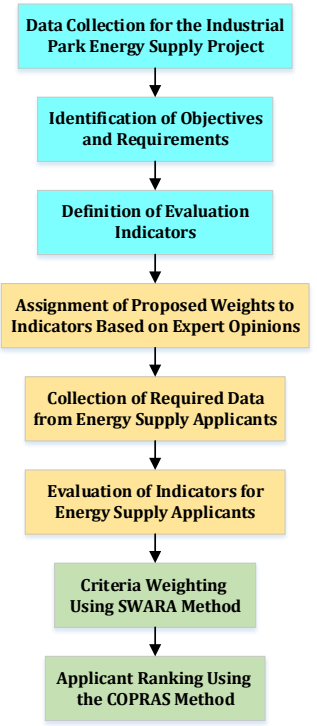


Figure 2. Flowchart of the ranking and selection process for the energy supplier company of the industrial microgrid from among the applicants.

4. Case Study and Validation Strategy

This section presents a simulated case study to demonstrate the practical application of the proposed SWARA + COPRAS framework for evaluating energy supplier companies in industrial microgrids. The objective is to calculate the final weights of evaluation criteria and rank applicants based on expert judgment.

It should be highlighted that, due to the proprietary nature of operational performance data and internal evaluation indicators, energy supplier companies do not readily disclose such information to external parties. As a result, obtaining empirical data from industrial parks or supplier firms was not feasible for this research. Accordingly, the present case study was developed based on hypothetical expert assessments designed to simulate realistic decision-making environments. Nevertheless, the proposed framework is fully scalable and can be deployed in real-world settings upon gaining access to such data.

To maintain clarity and focus, the case study applies the framework to a selected subset of indicators and sub-indicators introduced in Section 2. This choice avoids excessive computational volume and allows for a transparent demonstration of the methodology.

4.1. Weighting of Indicators Using the SWARA Method

Three domain experts rated the importance of main indicators and sub-indicators using a 1-to-5 scale (1 = least important, 5 = most important). Tables 5–8 present these ratings.

In the SWARA method, to determine the final weight of each main indicator, it is sufficient to divide the average of the weights provided by experts for each indicator by the sum of the averages of all indicators. Since the total sum of the average weights provided by experts for all main indicators is 15.67, the final weight of each main indicator for ranking applicants using the SWARA method is as follows:

Operational and Technical Indicator: 4.67/15.67 = 0.298

Investment and Economic Indicator: 4/15.67 = 0.255

Environmental Indicator: 4/15.67 = 0.255

Development and Future Outlook Indicator: 3/15.67 = 0.191

In the SWARA method, the process described at the beginning of this section for determining the relative weight of each sub-indicator under the main indicators is repeated.

Sub-indicators of the Operational and Technical Indicator (Total average of expert weights = 14):

Quality of Technical Design: 0.334

System Reliability: 0.238

Equipment Efficiency: 0.262

Supply Sustainability: 0.166

Sub-indicators of the Economic Indicator (Total average of expert weights = 15):

Financial Capability: 0.222

Proposed Financial Resources: 0.245

Financial Provision Plans: 0.222

Estimated Costs: 0.311

Sub-indicators of the Environmental Indicator (Total average of expert weights = 15.67):

CO_2 Emission Intensity: 0.298

NO_x Emission Intensity: 0.212

SO_x Emission Intensity: 0.17

CO Emission Intensity: 0.17

Particulate Matter Emission Intensity: 0.149

Table 5. Weighting of Main Criteria Based on Expert Opinions in the Case Study.

Main Indicators	Assigned Weights			
	Expert 1	Expert 2	Expert 3	Average
Technical & Operational	5	4	5	4.67
Economic	4	5	3	4
Environmental	3	4	5	4
Future Development & Flexibility	2	3	4	3

Table 6. Weighting of Technical and Operational Sub-Indicators Based on Expert Opinions for the Case Study.

Technical and Operational Sub-Criteria	Assigned Weights			
	Expert 1	Expert 2	Expert 3	Average
Technical Design Quality	5	4	5	4.67
System Reliability	3	4	3	3.33
Equipment Efficiency	4	3	4	3.67
Supply Sustainability	2	2	3	2.33

Table 7. Weighting of Economic Sub-Indicators Based on Expert Opinions in the Case Study.

Economic Sub-Criteria	Assigned Weights			
	Expert 1	Expert 2	Expert 3	Average
Financial Capability	3	4	3	3.33
Proposed Financial Resources	4	3	4	3.67
Financing Plans	3	4	3	3.33
Estimated Costs	5	5	4	4.67

The Development and Future Outlook Indicator does not have sub-indicators and therefore does not require weight calculation.

Finally, in the SWARA method, the final weight of the sub-indicators is calculated by multiplying the relative weight of each sub-indicator by the final weight of the main indicator.

The final weight of the Operational and Technical Indicator is 0.298, and based on the weights of its sub-indicators, we have:

Quality of Technical Design: 0.0995

System Reliability: 0.0709

Equipment Efficiency: 0.0781

Supply Sustainability: 0.0495

The final weight of the Investment and Economic Indicator is 0.255, and based on the relative weights of its sub-indicators, we have:

Financial Capability: 0.0566

Proposed Financial Resources: 0.0625

Financial Provision Plans: 0.0566

Estimated Costs: 0.0793

The final weight of the Environmental Indicator is 0.255, and based on the relative weights of its sub-indicators, we have:

CO_2 Emission Intensity: 0.076

NO_x Emission Intensity: 0.0541

SO_x Emission Intensity: 0.0434

CO Emission Intensity: 0.0434

Particulate Matter Emission Intensity: 0.038

The final weight of the Development and Future Outlook Indicator is 0.191, and based on its sub-indicator weight, we have:

Future Development and Flexibility Plans: 0.191

4.2. Selection of the Top Company Using the COPRAS Method

As mentioned in Section 2 of this paper, the steps of the COPRAS method include normalizing the decision matrix, forming the weighted decision matrix, calculating the positive and negative values, and calculating the final scores for the companies. In this stage, it is assumed that the quantitative evaluation of the sub-indicators for all main indicators has been carried out by the expert team. Finally, based on (4), the normalized decision matrix is calculated as shown in Table 9.

Table 8. Weighting of Environmental Sub-Indicators Based on Expert Opinions in the Case Study.

Environmental Sub-Criteria	Assigned Weights			
	Expert 1	Expert 2	Expert 3	Average
CO_2 Emission Intensity	5	4	5	4.67
NO_x Emission Intensity	3	3	4	3.33
SO_x Emission Intensity	2	3	3	2.67
CO Emission Intensity	3	2	3	2.67
Particulate Matter Emission Intensity	2	2	3	2.33

Table 9. The normalized values of the decision matrix for the case study.

Main Indicators	Sub-Indicators	Scores		
		Supplier A	Supplier B	Supplier C
Technical & Operational	Technical Design Quality	0.417	0.333	0.25
	System Reliability	0.308	0.385	0.308
	Equipment Efficiency	0.273	0.273	0.455
	Energy Supply Sustainability	0.286	0.286	0.429
Economic	Financial Capability	0.333	0.417	0.25
	Proposed Financial Resources	0.385	0.308	0.308
	Financing Plans	0.333	0.25	0.417
	Projected Costs	0.273	0.364	0.364
Environmental	CO_2 Emission Intensity	0.357	0.286	0.357
	NO_x Emission Intensity	0.357	0.364	0.364
	SO_x Emission Intensity	0.25	0.375	0.375
	CO Emission Intensity	0.571	0.286	0.143
	PM Emission Intensity	0.25	0.25	0.5
Future Development & Flexibility	Future Development Plans and Network Flexibility	0.417	0.333	0.25

In this step, using (5), the weighted matrix is formed by applying the sub-criteria weights obtained through the SWARA method. According to this equation, the weighted matrix is derived by multiplying the final weights of the sub-criteria (from SWARA) by the scores assigned to the applicant companies (as shown in Table 9). The resulting values are shown in Table 10.

After constructing the weighted matrix, the values of S^+ and S^- are calculated using the results from Tables 10 and 6 and 7. It should be noted that the environmental and greenhouse gas emission intensities are considered non-beneficial criteria, while the remaining criteria are treated as beneficial.

S^+ values for the three applicant companies are:

$$S_A^+ = 0.0415 + 0.0218 + 0.0213 + 0.0142 + 0.0188 + 0.0241 + 0.0188 + 0.0216 + 0.0796 = 0.2617 \quad (10)$$
$$S_B^+ = 0.0331 + 0.0273 + 0.0213 + 0.0142 + 0.0236 + 0.0192 + 0.0141 + 0.0289 + 0.0636 = 0.2453$$
$$S_C^+ = 0.0249 + 0.0218 + 0.0355 + 0.0212 + 0.0142 + 0.0192 + 0.0236 + 0.0289 + 0.0477 = 0.237$$

S^- values for the three applicant companies are:

$$S_A^- = 0.0148 + 0.0109 + 0.0095 + 0.0271 + 0.0248 = 0.0871 \quad (11)$$
$$S_B^- = 0.0197 + 0.0163 + 0.0095 + 0.0217 + 0.0124 = 0.0796$$
$$S_C^- = 0.0197 + 0.0163 + 0.0190 + 0.0271 + 0.0062 = 0.0883$$

Finally, the utility degree Q_i is calculated using (8), and the supplier companies are ranked accordingly.

$$\sum_{i=1}^{n} S_i^- = 0.0871 + 0.0796 + 0.0883 = 0.255 \quad (12)$$

$$\sum_{i=1}^{n} \frac{1}{S_i^-} = 35.369 \quad (13)$$

$$Q_A = 0.344 \quad (14)$$
$$Q_B = 0.336$$
$$Q_C = 0.318$$

Based on the results of Q_i, supplier Company A receives the highest score and is selected as the top-performing supplier company in the final ranking. This outcome can be attributed to its consistently strong results in high-priority beneficial criteria, particularly Technical Design Quality and Future Development Plans, coupled with solid economic performance and controlled levels in non-beneficial environmental indicators. Together, these factors maximised its S+ value while keeping S− at a moderate level, leading to the highest overall utility score among all candidates.

4.3. Comparative Evaluation with AHP + TOPSIS

To assess the robustness and relative performance of the SWARA + COPRAS framework, the same dataset of normalized sub-indicator scores (Table 9) was evaluated using the AHP + TOPSIS approach.

Step 1 – Weight derivation (AHP): The pairwise comparison matrix for the main criteria was constructed from the average expert ratings (Table 5). Consistency ratios were below the 0.1 threshold, confirming acceptable consistency. The resulting normalized weights were comparable to those obtained via SWARA, with slight deviations due to the pairwise structure of AHP.

Step 2 – TOPSIS ranking: Using the AHP-derived weights, the weighted normalized decision matrix was constructed. The positive ideal solution (PIS) and negative ideal solution (NIS) were identified, Euclidean distances to each were computed, and the relative closeness coefficient Ci was calculated (Table 11).

Table 10. COPRAS Weighted Matrix Using SWARA Weights in the Case Study.

Sub-Indicators	Supplier A	Supplier B	Supplier C
Technical Design Quality	0.0415	0.0331	0.0249
System Reliability	0.0218	0.0273	0.0218
Equipment Efficiency	0.0213	0.0213	0.0355
Energy Supply Sustainability	0.0142	0.0142	0.0212
Financial Capability	0.0188	0.0236	0.0142
Proposed Financial Resources	0.0241	0.0192	0.0192
Financing Plans	0.0188	0.0141	0.0236
Projected Costs	0.0216	0.0289	0.0289
CO_2 Emission Intensity	0.0271	0.0217	0.0271
NO_x Emission Intensity	0.0148	0.0197	0.0197
SO_x Emission Intensity	0.0109	0.0163	0.0163
CO Emission Intensity	0.0248	0.0124	0.0062
PM Emission Intensity	0.0095	0.0095	0.0190
Future Development Plans and Network Flexibility	0.0796	0.0636	0.0477

Table 11. Obtained Results from the AHP-TOPSIS Based Method.

Supplier	Ci	Rank
A	0.652	1
B	0.641	2
C	0.606	3

Both SWARA + COPRAS (with the custom Qi formulation) and AHP + TOPSIS independently identify Supplier A as the best performing company. This alignment across two distinct multi criteria decision making frameworks reinforces confidence in the result and suggests that A's competitive advantage is not an artefact of a single method's weighting or aggregation mechanics. Although both SWARA + COPRAS and AHP + TOPSIS produced consistent final rankings in this study, the proposed framework offers distinct advantages in terms of transparency, computational simplicity, and adaptability. SWARA enables direct expert scoring without requiring complex pairwise comparisons or consistency checks, while COPRAS allows flexible customization of the utility function to reflect domain-specific priorities. This makes the method particularly suitable for industrial decision-making contexts where expert input must be processed efficiently and where certain criteria, such as environmental or security-related indicators, may require tailored penalization schemes. Moreover, the linear structure of COPRAS facilitates straightforward sensitivity analysis, enhancing the interpretability and robustness of the evaluation process.

4.4. Sensitivity Analysis

To evaluate the robustness of the proposed SWARA + COPRAS framework, a sensitivity analysis was conducted by perturbing the weights assigned to the main criteria and observing the impact on the final ranking. In this regard, three scenarios were tested:

Scenario 1: Increasing the weight of the Environmental criterion by 20%, with proportional adjustment to the remaining criteria.

Scenario 2: Increasing the Economic criterion weight by 15%, with proportional reduction applied to other groups.

Scenario 3: Assigning equal weights to all main criteria.

In each case, sub-indicator weights were scaled linearly within their respective groups, and the resulting (S+) and (S-) values were recalculated accordingly. The final utility scores (Qi) were then computed using the modified inputs (as shown in Table 12).

The results demonstrate that Supplier A consistently maintained the top rank across all tested scenarios. This stability indicates that the ranking is not overly sensitive to moderate variations in expert-assigned weights and that Supplier A possesses a structural advantage in high-weight beneficial criteria. The robustness of the proposed framework under changing weight conditions reinforces its suitability for practical decision-making environments, particularly in industrial contexts where expert judgments may vary or evolve over time.

5. Conclusions

This paper examined the evaluation and ranking process of energy supplier companies for industrial microgrids. Given the increasing demand for energy and the need to optimize its consumption, microgrids have emerged as an efficient solution for providing sustainable and reliable energy. Private companies operating in this field play a key role in the development of these systems; therefore, evaluating and ranking them is essential for selecting the most suitable options. This process not only helps improve service quality but also assists industries in achieving their economic and technical goals.

To evaluate the companies, primary and secondary criteria were defined, including technical and operational, economic, environmental, service and customer commitment, managerial and organizational, and development and future-oriented indicators. Each criterion was further broken down into specific sub-criteria to enable a more precise assessment of company performance. Weighting was based on expert opinions using the SWARA method, which effectively integrates diverse perspectives and reaches consensus on indicator importance.

Companies were then evaluated using both quantitative and qualitative methods, and ranked using the COPRAS technique with a customized utility formulation. In the case study, three applicant companies were assessed, and the results showed that Company A achieved the highest utility score ($Q = 0.3445Q = 0.3445$), confirming its top performance. Comparative analysis with AHP + TOPSIS yielded consistent rankings, reinforcing the reliability of the proposed framework. Sensitivity analysis further demonstrated that the ranking remained stable under various weighting scenarios, validating the robustness of the approach.

Practical implications for policymakers and industrial park managers:

Use expert-driven scoring (SWARA) to simplify weighting and avoid inconsistency in pairwise comparisons.

Apply COPRAS with customizable utility functions to reflect strategic priorities such as environmental penalties or development goals.

Expect stable supplier rankings even under moderate shifts in expert judgment or policy emphasis.

Integrate the framework into procurement workflows to support transparent, multi-criteria supplier selection.

Table 12. Sensitivity Analysis Results.

Scenario	QA	QB	QC	Rank Order
Baseline	0.3445	0.3359	0.3187	A > B > C
Environmental +20%	0.3443	0.3374	0.3189	A > B > C
Economic +15%	0.3436	0.3360	0.3197	A > B > C
Equal Weights	0.3499	0.3366	0.3134	A > B > C

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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. The ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, redundancy, have been completely observed by the authors.

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