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Application Entropy Weighting and Simple Additive Weighting Methods for Load Ranking in Microgrid

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ABSTRACT

This paper presents the Entropy Weighting Method (EWM) combined with the Simple Additive Weighting (SAW) method to determine the optimal load among multiple loads, serving the purpose of load ranking in a microgrid system, taking into account the priority of supply reliability. Load ranking is essential for evaluating the importance level of each load in the power system, thereby enhancing the operational efficiency of the microgrid. EWM is employed to determine the objective weights of each criterion based on the degree of dispersion of the criteria in the decision matrix, followed by the application of the SAW method to calculate the final priority weight of each load. This weighting approach is straightforward to implement and helps to minimize the subjectivity of decision-makers, thereby improving the reliability of the ranking results. The computational results, applied to the IEEE 16-bus microgrid model, demonstrate the effectiveness of the proposed method.

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1. Introduction

Nowadays, to ensure the economic development of a nation, it is essential to have a secure and reliable energy supply. Over the past decade, Distributed Energy Resources such as solar panels, wind turbines, and hydropower have accelerated the growth of microgrid systems, aiming to enhance the safety and quality of electricity supply. Microgrid represents one of the intelligent power distribution networks for small-scale electricity delivery, capable of operating in conjunction with the main grid or independently. When integrated with the main grid, in the event of a grid failure, the microgrid system can automatically disconnect and switch to autonomous operation mode.

A critical factor in ensuring supply reliability within a microgrid system is load ranking. In microgrids, load ranking is an essential process that identifies and categorizes the importance of loads within the microgrid, prioritizing electricity supply to critical loads such as medical facilities, defense systems, and control centers under conditions of limited power supply due to energy shortages or system failures.

To address this challenge, numerous multi-criteria decision-making (MCDM) techniques have been proposed and widely applied. The VIKOR method, proposed in [1], is based on the compromise solution principle to derive results. However, both methods are sensitive to extreme data values and fail to account for correlations among criteria. Additionally, the study in [2] proposed the Fuzzy DEMATEL–ANP VIKOR method for ranking and shedding loads. While the combined approach yielded credible results, it was relatively complex and challenging to implement. Alternatively, the MOORA method [3] is simple and easy to compute, but does not consider inter-criteria correlations and struggles to determine criterion weights [4], [5]. The Best-Worst Method was introduced in [6], which reduces the evaluation burden on experts yet remains subjective. Another approach involves using the covariance matrix to determine priority weights, thereby minimizing subjectivity in expert opinions [7]. The Analytic Hierarchy Process (AHP) method [8] allows for the evaluation of criteria through pairwise comparisons. However, it still heavily relies on subjective judgment. To enhance the reliability of the results, the

Analytic Network Process (ANP) was developed, enabling interdependent relationships among criteria within a network [9]. Nevertheless, ANP remains incomplete due to its reliance on subjective pairwise comparisons, which may introduce inconsistencies and increase the computational burden as the number of criteria and interrelationships grows. In [10], [11], improvements to AHP were proposed to increase objectivity and enable more accurate weight calculations. On the other hand, these improvements significantly increase the complexity of the algorithm. The objective weighting method, the EWM has been developed [12] to determine weights without requiring input from decision-makers [13]; however, it is unsuitable for handling fuzzy data and does not capture correlations among criteria. Principal Component Analysis (PCA) is a technique that reduces data dimensionality while retaining important information and removing noise and redundancy [14], [15]. Nonetheless, since principal components are linear combinations, they are difficult to interpret and are unsuitable when variables have nonlinear relationships. The SAW method [16] offers notable advantages such as simplicity, ease of application, and reliable results. Therefore, it can be applied across various fields and is also well-suited for integration with other methods such as AHP and TOPSIS [17]–[19].

In this paper, a method for loads ranking in a microgrid prioritizing power supply reliability is presented by combining the EWM and SAW methods. The EWM method is used to calculate the weights of the criteria, and the SAW method is then used to compute the priority weights of power supply continuity for loads. Loads with higher priority weights are prioritized for power supply, while loads with lower priority weights are shed first. The method implemented in the paper helps increase objectivity in selecting options.

2. Literature Review

2.1. Multi-criteria decision-making

MCDM methods have been developed and are considered essential tools that enable decision-makers to select the optimal solution when multiple and often conflicting criteria are involved. MCDM methods vary in scope and approach and can generally be classified into two main categories: Multi-Attribute Decision-Making (MADM) and Multi-Objective Decision-Making (MODM) [20]. Specifically, MADM is applicable when the decision-maker needs to evaluate or select the best alternatives, whereas MODM is a suitable approach for evaluating continuous alternatives where constraints are defined in terms of decision variable vectors. An optimal output is obtained by considering a set of alternatives and performing an analysis that involves trade-offs, potentially reducing the performance of one or more objectives [21].

MCDM methods are mathematical approaches that consider multiple criteria and provide results to facilitate ranking based on their role in decision-making. These methods have been widely applied across various domains such as power systems, energy management, and even in the military sector [2], [21], [22]. Among MCDM methods, the subjective approach of the AHP, proposed by Saaty, is one of the most widely used. This method allows decision-makers to score alternatives using Saaty's 1–9 scale. However, a significant drawback of AHP is that the reliability of its results is limited, as most judgment matrices depend heavily on the subjective opinions of decision-makers. To overcome these limitations, the objective weighting method known as the EWM has been developed.

2.2. Entropy Weighting Method

In the MCDM process, determining the weights of criteria is an indispensable step, as it directly influences the outcome, ensuring that decisions are accurate and objective. Among the weighting determination methods, the EWM is one of the approaches that quantifies the degree of uncertainty or the level of dispersion among different information sources in decision-making. This method helps eliminate the subjectivity of decision-makers, thereby ensuring the reliability and objectivity of the ranking results. The primary purpose of EWM is to determine the weights of criteria objectively while still maintaining reliability. The computational procedure of the EWM, including decision matrix normalization, entropy value calculation, divergence degree determination, and criterion weight computation, is presented in Figure 1.

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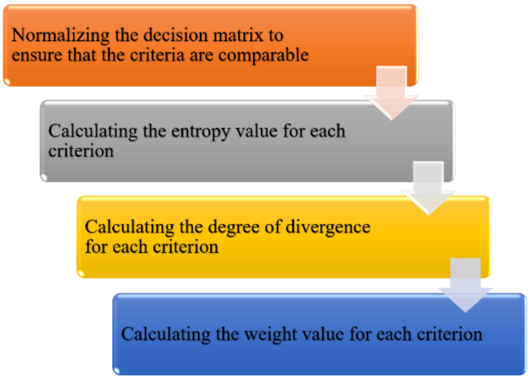

Figure 1. *Entropy Weighting method calculation process.*

The entropy weighting method has been applied in various fields such as assessing power quality in electrical systems, evaluating water quality indices, and assessing air quality indices [23], [13], [20]. In addition to studies on the traditional EWM approach, recent research has integrated EWM with other MCDM methods such as AHP, SAW, and fuzzy TOPSIS to facilitate alternative ranking.

EWM is an important method applied in multi-criteria decision-making problems, enabling decision-makers to determine objective weights and enhance the reliability of the ranking results.

2.3. Simple Additive Weighting

Among ranking methods, the SAW method is known as one of the classical MADM approaches and is among the most widely applied due to its simplicity and ease of implementation. The principle of computation in the SAW method involves normalizing the criteria so that they become comparable, followed by calculating the total weight by multiplying the normalized criteria by their respective weights. Essentially, applying the SAW method entails determining the total weighted score of each alternative based on the criteria, with the alternative achieving the highest total weight considered the optimal choice. The computational steps of the SAW method, including decision matrix normalization, priority weight calculation, and alternative ranking, are presented in Figure 2.

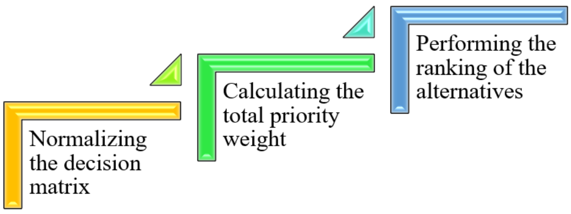

Figure 2. *Simple Additive Weighting method calculation process.*

The SAW method is widely applied in almost all fields due to its simplicity and ease of application. In paper [24], the SAW method is used in education, while in [25], the SAW method is used for personnel selection. The SAW method is also combined with other MCDM methods such as AHP, TOPSIS, WP [26], [19], and [27].

Although SAW is a simple method, it plays an important role in ranking within MCDM. Its advantages lie in its transparency and reliability, which contribute to enhancing the credibility of the ranking results.

3. Methodology

3.1. Data collection

3.1.1. Determine the Load Importance Factor (LIF)

The LIF is a criterion used in load ranking and evaluation. Determining the load importance factor is essential for managing and ensuring the continuity of the power supply. Loads with higher importance factors will have less power curtailed. Based on previous research [28], the calculated load importance factor is utilized in conjunction with the voltage sensitivity index and voltage distance to facilitate load ranking.

3.1.2. Determine the Voltage Electrical Distance (VED)

Based on previous research [28], the method for determining the VED is presented. From a mathematical perspective, the VED between two buses is calculated using the following Equation (1):

$$D_V(i,j) = D_V(j,i) = -Log(\alpha_{ij} \times \alpha_{ji}) \tag{1}$$

Where α_{ij} represents the influence of a voltage variation at bus j on bus i, while α_{ji} represents the influence of a voltage variation at bus i on bus j.

To determine the weights of loads according to the VED criterion, the VED values need to be normalized using the following Equation (2) [28]:

$$W_{VED_i} = \frac{D_{V(i,j)}}{\sum_1^m D_{V(i,j)}} \tag{2}$$

3.1.3. Determine the Voltage Sensitivity Index (VSI)

According to the research conducted by the authors [28], the VSI value at the load bus is calculated as Equation (3):

$$VSI_i = \sqrt{\frac{\sum_{k=1}^n (1-V_k)^2}{n}} \tag{3}$$

The VSI value is normalized according to the following equation to calculate the weight of loads as Equation (4) [28]:

$$W_{VSI_i} = \frac{VSI_i}{\sum_1^m VSI_i} \tag{4}$$

3.2. Entropy Weighting Method

The EWM is an objective approach for determining the weights of criteria in the decision-making process. Its purpose is to identify the relative importance of the criteria, specifically based on the degree of variation or uncertainty of the data. By utilizing the collected data, this method analyzes the degree of dispersion of the criteria values. Criteria with larger variations in their evaluation values provide more information, as they contribute more significantly to distinguishing among alternatives, and vice versa [17].

Step 1: In the Entropy method, a decision matrix is formed by synthesizing evaluation data from each alternative against some criteria as Equation (5) [17]:

$$X = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix} \tag{5}$$

Step 2: Normalize the decision matrix using formula as Equation (6) [17]:

$$k_{ij} = \frac{x_{ij}}{\sum_{i=1}^m x_{ij}} \tag{6}$$

Step 3: Calculate the Entropy value for each criterion using Equation (7) [17]:

$$E_j = -\frac{1}{\ln(m)} \sum_{i=1}^{m} k_{ij} \times \ln(k_{ij}) \tag{7}$$

Step 4: The divergence level is used to evaluate the amount of information each criterion provides in distinguishing between alternatives. The divergence level value is calculated using the Equation (8) [17]:

$$D_j = 1 - E_j \tag{8}$$

Step 5: The weights of criteria are used to determine the relative importance of each criterion in the decision-making process. The weight value for each criterion is calculated using the Equation (9) [17]:

$$w_j = \frac{D_j}{\sum_{j=1}^{n} D_j} \tag{9}$$

The main purpose of the Entropy method is to objectively calculate the weights of criteria, which are then combined with the SAW method to rank loads.

3.3. Simple Additive Weighting method

The SAW method, also known as the weighted linear combination method or the scoring method, is one of the simplest and most widely used multi-criteria decision-making techniques. This method is based on the weighted average approach. A score for each alternative is calculated by multiplying its normalized value for each criterion by the corresponding importance weight assigned directly by the decision-maker, and then summing these products across all criteria. An advantage of this method is that it represents a proportional linear transformation of the original data, meaning that the relative order of magnitude of the normalized scores is preserved [25]. The procedure for implementing this method is as follows:

Step 1: Construct a decision matrix, then normalize the criteria of the matrix:

- For positive criteria:

$$n_{ij} = \frac{x_{ij}}{x_j^{\max}} \quad \text{i=1,...m,} \quad \text{j=1,...n} \tag{10}$$

- For negative criteria:

$$n_{ij} = \frac{x_j^{\min}}{x_{ij}} \quad \text{i=1,...m,} \quad \text{j=1,...n} \tag{11}$$

Step 2: A simple additive weighting method will produce the final priority value, using the Equation (12):

$$S_i = \sum_{j=1}^{n} w_j \times n_{ij} \tag{12}$$

After the SAW calculation, each load receives a priority score reflecting how good that load is for the defined overall criteria. The priority value is obtained by summing the products of the Entropy weights and the normalized values for each criterion. The load with the highest score is considered the best, as it demonstrates the strongest overall performance. This process helps decision-makers rank loads to prioritize power supply in the most objective manner.

4. Results

The model employed in this study is the IEEE 16-bus microgrid system, comprising three main load areas with 8 loads and 6 generation sources [28], as illustrated in Figure 3.

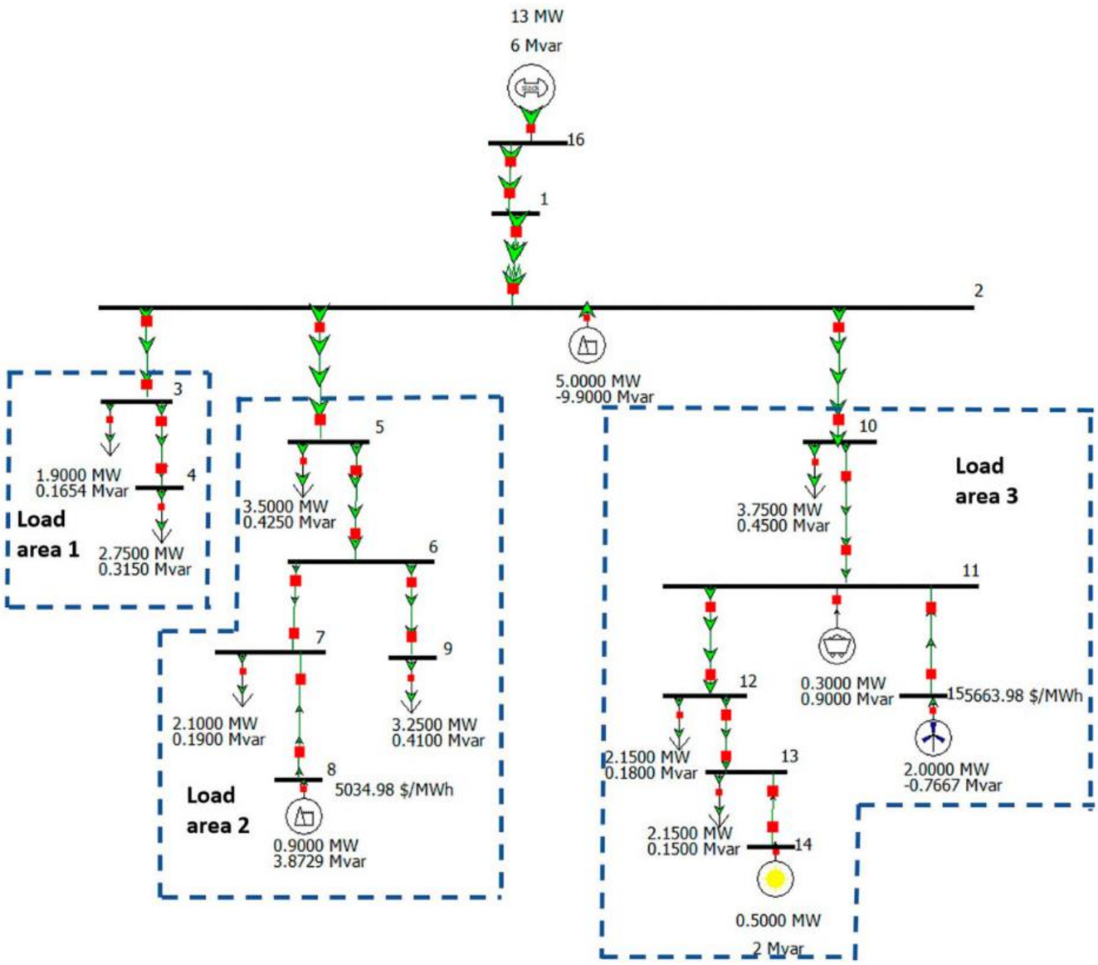

Figure 3. *Single-line diagram of Microgrid IEEE 16-bus [28].*

The data used in this study were obtained based on the results presented in [28] by applying Eqs. (1)–(4), as shown in Table 1. The LIF, VED, and VSI values presented in Table 1 and the subsequent tables are dimensionless normalized indices rather than physical quantities with specific units. These indices are used to evaluate the relative priority of the loads according to the corresponding criteria.

Table 1. *Data values of the criteria.*

Load	LIF	VED	VSI
L3	0.329	0.10965	0.12830
L4	0.164	0.13459	0.10152
L5	0.032	0.09850	0.13119
L7	0.106	0.13640	0.12686
L9	0.058	0.13896	0.11813
L10	0.038	0.10964	0.13097
L12	0.099	0.13099	0.13135
L13	0.174	0.14126	0.13168

To clarify the proposed method, based on the characteristic data of the loads and three criteria (LIF, VED, VSI) presented in Table 1, the proposed approach constructs the following decision matrix:

$$X=\begin{bmatrix}0.329 & 0.10965 & 0.1283\\ 0.164 & 0.13459 & 0.10152\\ 0.032 & 0.0985 & 0.13119\\ 0.106 & 0.1364 & 0.12686\\ 0.058 & 0.13896 & 0.11813\\ 0.038 & 0.10964 & 0.13097\\ 0.099 & 0.13099 & 0.13135\\ 0.174 & 0.14126 & 0.13168\end{bmatrix}$$

From the above matrix, each value is normalized to allow for proportional comparison. By applying the normalization process using Equation (6), the entropy value for each criterion is calculated based on Equation (7). Subsequently, the degree of divergence and the entropy weight values are determined using Equations (8) and (9), with the results presented in Table 2.

$$k_{11}=\frac{x_{11}}{\sum_{i=1}^{m}x_{11,81}}=\frac{0.329}{0.329+0.164+0.032+0.106+0.058+0.038+0.099+0.174}=\frac{0.329}{1}=0.329$$

$$E_1=-\frac{1}{\ln(8)}\sum_{i=1}^{m}k_{11,81}\times\ln(k_{11,81})=(-0.4809)\times(-1.8329)=0.8814$$

$$D_1=1-E_1=1-0.8814=0.1186$$

$$w_1=\frac{D_1}{\sum_{j=1}^{n}D_{1,3}}=\frac{0.1186}{0.1186+0.0037+0.0016}=0.9572$$

Table 2. *Entropy values, divergence degrees, and Entropy weights for each criterion.*

Load	LIF	VED	VSI
L3	0.329	0.10965	0.12830
L4	0.164	0.13459	0.10152
L5	0.032	0.09850	0.13119
L7	0.106	0.13640	0.12686
L9	0.058	0.13896	0.11813
L10	0.038	0.10964	0.13097
L12	0.099	0.13099	0.13135
L13	0.174	0.14126	0.13168
E_j	0.8814	0.9963	0.9984
D_j	0.1186	0.0037	0.0016
w_j	0.9572	0.0300	0.0128

The normalization of the decision matrix using the SAW method is performed for the criteria based on Equation (10), with the results presented in Table 3.

$$n_{11}=\frac{x_{11}}{x_1^{\max}}=\frac{0.329}{0.329}=1$$

Table 3. *Normalized values of the decision matrix using the SAW method.*

Load	LIF	VED	VSI
L3	1	0.77622823	0.97433171
L4	0.49848024	0.95278210	0.77095990
L5	0.09726444	0.69729577	0.99627886
L7	0.32218845	0.96559536	0.96339611
L9	0.17629179	0.98371797	0.89709903
L10	0.11550152	0.77615744	0.99460814
L12	0.30091185	0.92729718	0.99749392
L13	0.52887538	1	1

After normalizing the decision matrix using the SAW method, the next step is to calculate the final priority value for each criterion using Equation (12), with the final results presented in Table 4.

$$\begin{aligned} S_1 &= \sum\nolimits_{j=1}^{n} w_{1,3} \times n_{11,13} \\ &= (0.9572\times 1) + (0.03\times 0.77622823) + (0.013\times 0.97433171) \\ &= 0.9932 \end{aligned}$$

Table 4. *Total priority value for each load.*

Load	L3	L4	L5	L7	L9	L10	L12	L13
S_i	0.9932	0.5156	0.1267	0.3497	0.2097	0.1465	0.3285	0.549

By analyzing the ranking results obtained using the combined EWM and SAW method, it can be observed that each load is evaluated based on its total priority value, calculated as the sum of the normalized values of each criterion multiplied by the corresponding entropy weight. The load with the highest priority score is considered the most critical and is ranked first. Accordingly, based on the results in Table 4 the load ranking in the Microgrid can be determined as follows:

$$L3 \succ L13 \succ L4 \succ L7 \succ L12 \succ L9 \succ L10 \succ L5$$

Table 5. *Summary of the evaluation of the methods.*

Criteria	**AHP**	**Fuzzy VIKOR**	**EWM - SAW**
Handling uncertainty	Does not handle fuzzy data; criteria are evaluated based on the “1–9” scale	Capable of handling fuzzy data	Cannot handle fuzzy data
Dependence on expert opinions	High dependence, mainly relying on expert judgment	Moderate dependence, relying on fuzzy data evaluation	Independent of expert judgment
Computational capability	Complex, requires numerous pairwise comparisons	Complex, involves complicated computational steps	Simple, computational steps are straightforward to implement
Computational Time	Moderate, due to extensive pairwise comparisons	High, due to fuzzy processing and multiple complex calculation steps	Low, due to linear and non-iterative structure

Accuracy	Depends on subjective judgment, may introduce bias	High in uncertain environments	Stable and consistent for linear data
Stability	Low, sensitive to inconsistencies in evaluation	Moderate, depends on fuzzy parameters and input data	High, due to deterministic and non-iterative structure

The load ranking results obtained using the EWM combined with the SAW method presented in this paper are compared with two other methods, namely AHP [28] and Fuzzy VIKOR [29]. The evaluation methods are summarized in Table 5, and the corresponding results are presented in Table 6. Across these methods, the comparison consistently ranks Load 3 highest. However, the rankings of the other loads show slight variations among the three methods. This difference may be attributed to the less effective handling of conflicting criteria in AHP and Fuzzy VIKOR, as well as the continued reliance on expert judgment for evaluating criteria. The EWM–SAW method is introduced for ranking to overcome the subjectivity limitations of AHP and Fuzzy VIKOR, while the use of SAW for ranking also enables faster problem-solving.

Table 6. *Comparison of ranking results among the methods.*

Load	**AHP**	**Fuzzy VIKOR**	**EWM - SAW**
	Rank	***Rank***	***Rank***
Load 3	1	1	1
Load 4	2	2	3
Load 5	8	7	8
Load 7	4	4	4
Load 9	6	6	6
Load 10	7	8	7
Load 12	5	5	5
Load 13	3	3	2

5. Discussion

This paper presents a method that combines EWM and SAW for load ranking in microgrid systems. By employing EWM to determine the weights of criteria objectively, the approach helps minimize bias in decision-making. Subsequently, SAW is applied to compute the final priority weights, most simply to facilitate load ranking. However, when applied to large-scale power networks with an increasing number of loads and operational scenarios, the entropy-based weighting process and data updates may increase computational time. Additionally, the assumption of a static decision matrix in the SAW method restricts adaptability in rapidly changing operating conditions.

The research results indicate that integrating EWM and SAW can enhance the objectivity and reliability of the ranking outcomes. Unlike the AHP method, which still relies on pairwise comparisons of criteria and subjective expert judgments, or the Fuzzy VIKOR method, which effectively handles fuzzy data but involves a highly complex computation process, the EWM–SAW method offers notable advantages in terms of computational simplicity and independence from subjective opinions. It is not intended to claim universal optimality over methods such as AHP or Fuzzy VIKOR, but rather to provide a simple, objective, and efficient approach for load ranking. In time-critical scenarios such as power shortages or grid faults, its non-iterative structure enables fast and reliable decisions, making it suitable for decision-support applications. However, this method still has limitations: both EWM and SAW are unsuitable for fuzzy datasets and fail to reflect interrelationships among criteria. Moreover, combining SAW with a subjective weighting method may lead to unstable results.

Specifically, the EWM assumes that the input data are deterministic and evaluates the importance of criteria based on their statistical dispersion. Therefore, it does not fully capture ambiguous or subjective factors, such as load priority derived from operational experience. Meanwhile, the SAW method employs a linear aggregation model that assumes a deterministic relationship between criteria and priority levels, making the ranking results sensitive to measurement errors and data fluctuations.

The proposed method is designed for deterministic, independent criteria, which may limit its applicability when data are uncertain. The independence assumption simplifies the model and may not capture complex interrelationships in real-world microgrid systems. However, it ensures computational efficiency and supports a simple and effective load ranking approach.

The EWM–SAW method is based on linear weighted aggregation and is suitable for normalized quantitative criteria, while qualitative data would require appropriate scaling or fuzzy-based extensions, which are outside the scope of the method as presented here. Nonlinear relationships among criteria can be addressed indirectly through preprocessing, even when they are not explicitly modeled. In terms of scalability, the method exhibits linear computational complexity, ensuring efficiency for large-scale systems; however, inter-criteria correlation and data sensitivity may affect ranking reliability rather than causing system instability. These limitations can be mitigated through criterion selection, improved normalization, sensitivity analysis, or integration of fuzzy or scenario-based approaches.

To further develop this approach, future research should consider the interdependencies among criteria, integrating fuzzy logic techniques to handle fuzzy data more effectively, as well as combining it with methods that account for inter-criteria relationships, such as DEMATEL or PCA, to eliminate noisy data and enhance result accuracy. The proposed method can also be integrated into a microgrid energy management system as a decision-support module. Operational data collected from the system can then be periodically processed to generate load priority rankings under near real-time conditions. Due to its low computational complexity, the proposed approach is suitable for supporting operational decisions such as load shedding and demand response.

6. Conclusion

This paper presents a method for loads ranking in a microgrid system. The combined EWM and SAW approach provides an objective and effective decision-making process for ranking. Priority weights for continuous power supply to the loads are calculated using the EWM method, and the SAW method is then applied to determine the loads' priority weights and their relative importance compared with other loads, thereby establishing a reliable load supply priority ranking. Calculating the priority weights using EWM eliminates the influence of subjective expert opinions, thereby ensuring accurate and reliable results.

However, the EWM method is not suitable for handling ambiguous or fuzzy data, as such datasets may distort the calculation of priority weights. Additionally, the SAW method relies on a linearity assumption, meaning that its application to certain criteria with qualitative or uncertain structures may lead to inaccurate results.

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Conflict of Interest

The authors declare no conflict of interest.

Data Availability Statement

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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