An Optimized Load Shedding Strategy Using Fuzzy MOORA Ranking

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ABSTRACT

Ensuring the stability and reliability of power systems under fault conditions and power imbalances remains a critical challenge in modern electrical networks. Among various mitigation techniques, selective Load Shedding (LS) is recognized as an effective method for restoring the system balance. However, identifying which loads to shed involves complex trade-offs among technical constraints, system priorities, and economic impacts. This paper proposes a novel Multi-Criteria Decision-Making (MCDM) approach based on Fuzzy Multi-Objective Optimization by Ratio Analysis under a Fuzzy Environment (MOORA) to improve the LS strategies. The integration of fuzzy logic enables the method to handle uncertainty and vagueness in real-time operational data, thereby enhancing decision robustness and adaptability. The proposed approach maintains the computational simplicity while ensuring an accurate load ranking based on multiple conflicting criteria. To validate the method, it is applied to a 16-bus microgrid model under various fault scenarios. Simulation results demonstrate that the method enhances system stability, reduces unnecessary economic losses, and improves the precision of load prioritization. These findings indicate that the approach is not only practical and scalable, but also highly suitable for intelligent load management in smart grid applications.

Keywords-fuzzy; MOORA; load ranking; load shedding; microgrid

I. INTRODUCTION

LS is a critical control strategy employed to prevent the cascading failures and total system collapse by selectively disconnecting the non-essential loads. The selection of loads to curtail plays a key role in the effectiveness of LS. MCDM methods have proven useful in addressing this challenge by enabling prioritization based on various technical and operational factors. Approaches, such as the Analytic Hierarchy Process (AHP) [1] and the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) [2] have been applied to prioritize the loads by combining the economic and technical criteria. However, these methods typically rely on crisp input values and fail to manage the uncertainties inherent in real-world power systems. While the fuzzy grey DEMATEL method provides valuable insights into the interrelationships among the risk factors, it may not be suitable for real-time or large-scale microgrid applications [3]. Other approaches, such as the fuzzy DEMATEL–ANP–VIKOR method, capture the inter-criteria dependencies and achieve robust rankings through fuzzy evaluation [4]. Similarly, fuzzy AHP combined with fuzzy load profiles has been proposed to mitigate the uncertainty in expert judgments [5]. These works support the current study's decision to embed fuzzy sets within the MOORA framework, thereby enhancing the ability to handle the uncertainty and improving the decision-making stability in dynamic microgrid environments.

To address these limitations, this study proposes an MCDM approach using Fuzzy MOORA for load ranking and optimal shedding decisions. Integrating fuzzy logic into the MOORA framework improves the handling of uncertainties and subjective evaluations associated with load importance. The methodology is tested on a 16-bus microgrid model, demonstrating its effectiveness in maintaining the system stability while optimizing the economic efficiency.

The proposed method considers key indicators, including the Load Importance Factor (LIF), Voltage Deviation (VED), and Voltage Sensitivity Index (VSI), each modeled using fuzzy sets and membership functions to capture the uncertainty and vagueness in the evaluation data [6]. Through a structured computational process, Fuzzy MOORA produces a ranked list of loads based on fuzzy evaluation scores, enabling an optimized and adaptive decision-making for power distribution. The methodology begins by defining the linguistic variables to classify the loads into different priority levels. These variables facilitate the creation of a fuzzy decision matrix, which serves as the foundation for further analysis and prioritization.

Fuzzy MOORA not only prioritizes the critical loads, but also enhances the overall reliability of microgrid power systems [7]. Unlike traditional LS techniques that rely on rigid frequency-based thresholds, the proposed approach balances the technical stability with economic efficiency while maintaining the computational simplicity. Its lightweight computational model ensures an easy implementation across diverse microgrid configurations, making it a scalable and practical solution for intelligent load management. By combining uncertainty handling, adaptive ranking, and ease of use, Fuzzy MOORA offers a comprehensive and efficient framework for optimizing the load prioritization and power distribution in modern microgrids.

II. METHODOLOGY FOR LOAD RANKING USING FUZZY MOORA

A flowchart of the proposed optimized LS based on Fuzzy MOORA is shown in Figure 1. The implementation of the Fuzzy MOORA method follows a structured computational process, which consists of the following key steps [8]:

A. Step 1: Problem Definition and Decision Group Formation

Initially, a group of decision-makers (DM1, DM2, DM3) is established to assess and rank the alternatives. In this context, m represents the number of alternatives (load options), and n represents the evaluation criteria, which are determined based on the system parameters. Each alternative is evaluated using linguistic variables, which are defined in Table I, to represent the subjective assessments in a structured manner. Additionally, the weights of the criteria are assigned using linguistic variables, based on evaluated data characteristics from prior research [6]. These linguistic variables are represented as Triangular Fuzzy Numbers (TFNs) with the membership functions defined in [9], ensuring flexibility in processing the subjective assessment data provided by decision-makers while minimizing the inconsistencies in evaluation.

TABLE I. LINGUISTIC VARIABLE USES FOR EVALUATING ALTERNATIVES AND CRITERIA

Linguistic variables	Criteria TFNs	Load TFNs
Very Low (VL)	(0, 0, 0.1)	(0, 0, 1)
Low (L)	(0, 0.1, 0.3)	(0, 1, 3)
Medium Low (ML)	(0.1, 0.3, 0.5)	(1, 3, 5)
Medium (M)	(0.3, 0.5, 0.7)	(3, 5, 7)
Medium High (MH)	(0.5, 0.7, 0.9)	(5, 7, 9)
High (H)	(0.7, 0.9, 1)	(7, 9, 10)
Very High (VH)	(0.9, 1, 1)	(9, 10, 10)

TFNs are employed to represent the linguistic values due to their ease of computation, intuitive nature, and established effectiveness in numerous MCDM applications. TFNs are applied to both the criterion weights and alternative evaluations, based on the linguistic variables defined in Table I. These fuzzy representations enable clear identification of the fuzzy sets corresponding to each linguistic term [10]. Table I presents the linguistic variables used to assess the criteria and their associated weights, along with the corresponding TFNs. For instance, the term "Very Low" is represented by the TFN (0, 0, 0.1), where 0 denotes the lowest and most probable value, and 0.1 indicates the upper bound of the "Very Low" range. Similarly, the term "Medium" is represented by the TFN (0.3, 0.5, 0.7), indicating a central value of 0.5 and a range extending from 0.3 to 0.7.

B. Step 2: Aggregation of Decision-Maker Evaluations and Construction of the Decision Matrix

Once the alternatives and criteria have been evaluated by the decision-makers, the next step is to aggregate their assessments into a single representative value. This process helps to reduce the variability and unify the subjective judgments into a structured format. To achieve a fuzzy decision matrix, (1) and (2) are applied accordingly [9, 11] to compute the aggregated fuzzy values for both the alternatives and criteria:

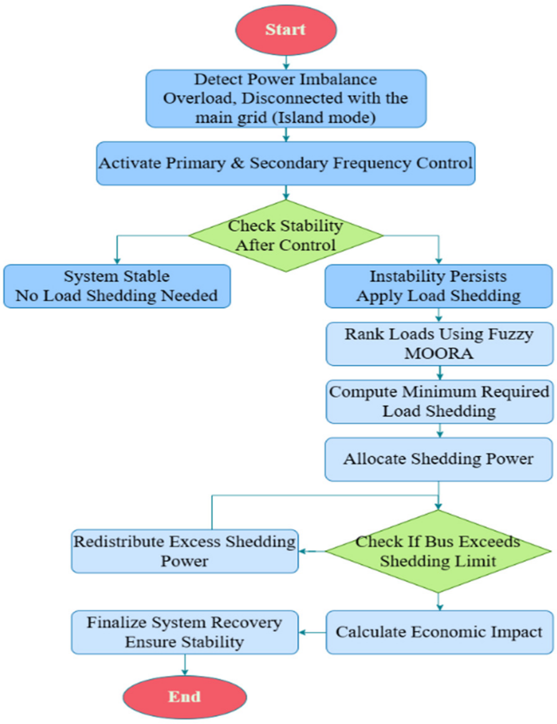

Fig. 1. Flowchart of the optimized LS method.

$$\tilde{x}_{ij} = \frac{1}{k}\left[\tilde{x}_{ij}^{1} \oplus \tilde{x}_{ij}^{2} \oplus \cdots \oplus \tilde{x}_{ij}^{k}\right] \quad (1)$$

where $\tilde{x}_{ij}$ represents the evaluation score of the i_{th} alternative under the j_{th} criterion, as assessed by the k_{th} decision-maker.

$$\widetilde{w}_j = \frac{1}{k}\left[\widetilde{w}_j^{1} \oplus \widetilde{w}_i^{2} \oplus \cdots \oplus \widetilde{w}_j^{k}\right] \quad (2)$$

where $\widetilde{w}_j$ represents the evaluation score assigned by the k_{th} decision-maker for j_{th} criterion.

C. *Step 3: Formation of the Fuzzy Decision Matrix and Fuzzy Weight Vector*

Once a single aggregated value has been obtained for all criteria and alternatives, the fuzzy decision matrix $\widetilde{D}$ and the fuzzy weight vector $\widetilde{W}$ are constructed as expressed in:

$$\begin{cases} \widetilde{W} = [\widetilde{w}_1 \quad \widetilde{w}_2 \ldots \quad \widetilde{w}_n] \\ \widetilde{D} = \begin{bmatrix} \tilde{x}_{11} & \tilde{x}_{12} \ldots & \tilde{x}_{1n} \\ \tilde{x}_{21} & \tilde{x}_{22} \ldots & \tilde{x}_{2n} \\ \vdots & \vdots \quad \ldots & \vdots \\ \tilde{x}_{m1} & \tilde{x}_{m2} & \tilde{x}_{mn} \end{bmatrix} \end{cases} \quad (3)$$

D. *Step 4: Normalization of Fuzzy Numbers*

In this step, the fuzzy numbers are normalized to ensure they have a consistent range and are uniform in the form of $\tilde{R}$.

$$\tilde{R} = \left[\tilde{r}_{ij}\right]_{m \times n} \quad (4)$$

where the values of $\tilde{r}_{ij} = \left(\tilde{r}_{ij}^{l},\ \tilde{r}_{ij}^{m},\ \tilde{r}_{ij}^{u}\right)$, l is the lower bound, m is the midpoint, and u is the upper bound of the TFNs, which are obtained using:

$$\tilde{r}_{ij}^{l} = \frac{x_{ij}^{l}}{\sqrt{\sum_{m}^{1}\left[\left(x_{ij}^{l}\right)^2 + \left(x_{ij}^{m}\right)^2 + \left(x_{ij}^{u}\right)^2\right]}} \quad (5)$$

$$\tilde{r}_{ij}^{m} = \frac{x_{ij}^{m}}{\sqrt{\sum_{m}^{1}\left[\left(x_{ij}^{l}\right)^2 + \left(x_{ij}^{m}\right)^2 + \left(x_{ij}^{u}\right)^2\right]}} \quad (6)$$

$$\tilde{r}_{ij}^{l} = \frac{x_{ij}^{u}}{\sqrt{\sum_{m}^{1}\left[\left(x_{ij}^{l}\right)^2 + \left(x_{ij}^{m}\right)^2 + \left(x_{ij}^{u}\right)^2\right]}} \quad (7)$$

E. *Step 5: Formation of the Overall Matrix*

The overall matrix $\tilde{V}$ is formed by multiplying the normalized fuzzy decision matrix $\tilde{R}$ with the fuzzy weight vector $\widetilde{W}$, as presented in (8). This step integrates the importance of each criterion into the decision-making process, ensuring that the weighted values accurately reflect the influence of different criteria within the Fuzzy MOORA framework:

$$\tilde{V} = \left[\tilde{v}_{ij}\right]_{m \times n} \quad (8)$$

with $\tilde{v}_{ij} = \tilde{r}_{ij} \otimes \widetilde{w}_j$ and $\tilde{v}_{ij} = \left(\tilde{v}_{ij}^{l},\ \tilde{v}_{ij}^{m},\ \tilde{v}_{ij}^{u}\right)$.

F. *Step 6: Calculation of the Overall Ranking for Benefit and Cost Criteria*

In this step, the overall ranking for both the benefit and cost criteria is determined for each alternative. For the benefit criteria, the overall ranking scores for the lower bound (l), midpoint (m), and upper bound (u) values are computed using (9). For the cost criteria, the overall ranking scores using (10):

$$s_i^{+l} = \sum_{j=1}^{n} v_{ij}^{l} \,\middle|\, j \in J^{max}, s_i^{+m} = \sum_{j=1}^{n} v_{ij}^{m} \,\middle|\, j \in J^{max}, s_i^{+u} = \sum_{j=1}^{n} v_{ij}^{u} \,\middle|\, j \in J^{max} \quad (9)$$

$$s_i^{-l} = \sum_{j=1}^{n} v_{ij}^{l} \,\middle|\, j \in J^{max}, s_i^{-m} = \sum_{j=1}^{n} v_{ij}^{m} \,\middle|\, j \in J^{max}, s_i^{-u} = \sum_{j=1}^{n} v_{ij}^{u} \,\middle|\, j \in J^{max} \quad (10)$$

G. *Step 7: Determination of the Overall Performance Index*

In this step, the overall performance index (SI) for each alternative is determined. To achieve this, the deviation values of the overall ranking scores for the benefit and cost criteria are calculated for each alternative. These calculations are performed using the vertex method, as defined in the following equations [9].

This step ensures that the final ranking accurately reflects the trade-off between maximizing the benefits and minimizing the costs, leading to an optimal prioritization of alternatives.

$$S_i(S_i^{+}, S_i^{-}) = \sqrt{\frac{1}{3}\left[(s_i^{+l} - s_i^{-l})^2 + (s_i^{+m} - s_i^{-m})^2 + (s_i^{+u} - s_i^{-u})^2\right]} \quad (11)$$

H. Step 8: Final Ranking of Alternatives

Finally, the alternatives are ranked based on their SI values. The alternative with the highest SI value is assigned to the highest rank, indicating the most optimal choice.

III. PROPOSED LS CONTROL BASED ON RANKING THE RESULTS

This study proposes an LS strategy to address the overloads, voltage collapse, and frequency instability in a microgrid system. A disconnection from the main power grid is simulated using Power World, where the Fuzzy MOORA method is applied to rank the loads for shedding. The goal is to restore the frequency and voltage stability while minimizing the economic impact on both the system operators and end-users.

By integrating MCDM, optimal priority weights are assigned to each load bus, reflecting their relative importance. This enables the precise calculation of the shedding power at each bus, ensuring that the minimum required load reduction is achieved. The approach aims to reduce the economic losses while maintaining the technical feasibility and system stability.

Modern power systems operate under both economic constraints and stability limits. The safe system operation depends on maintaining the frequency and voltage within allowable ranges. In abnormal conditions, such as loss of generation due to depleted reserves, sudden load surges, or instability from Renewable Energy Sources (RERs), the balance between the load demand and power generation is disrupted, causing frequency drops. When the primary and secondary controls fail to restore the system frequency, an LS stage is initiated. The final step involves disconnecting the non-essential loads to stabilize the system [12–14].

A. Load Shedding Allocation and Priority Ranking

The LS power at each bus is determined by:

$$P_{shed,k} = P_{shed,total} \times W_{priority,k} =$$

$$P_{shed,total} \times \frac{\frac{1}{S_{i,k}}}{\sum_{i=1}^{k} \frac{1}{S_{i,k}}} \qquad (12)$$

where $P_{shed,k}$ is the shedding power allocated to bus k, $P_{shed,total}$ is the total sheeding power required [6], and $W_{priority,k}$ is the priority weight of each bus, derived from the SI values of the Fuzzy MOORA ranking.

The priority ranking ensures that the loads with a lower importance and higher voltage sensitivity are shed first, minimizing the impact on the critical loads.

B. Economic Considerations: Penalty Costs for LS

The penalty cost associated with LS is computed using (13), with $c_{load,k}$ being the cost per MWh of LS at bus *k*. Minimizing $C_{penalty,k}$ ensures that the LS strategy is both technically and economically efficient:

$$C_{penalty,k} = P_{shed,k} \times c_{load,k} \qquad (13)$$

IV. RESULTS AND DISCUSSION

The case study focuses on the implementation of an LS strategy in an IEEE 16-bus power system [6], which is integrated with a microgrid consisting of multiple Distributed Energy Resources (DERs). To implement the Fuzzy MOORA approach for load ranking, initially, the key load characteristics are collected. These characteristics are evaluated based on three primary criteria: Importance of the Load (W_{LIF}), which represents the priority level of each load, with critical loads being assigned higher weights; Voltage Electrical Distance (W_{VED}), which measures the electrical proximity of the load to the faulted bus, influencing its impact on stability; and VSI (W_{VSI}), which reflects the load's response to the voltage fluctuations, where higher sensitivity means higher risk instability.

TABLE II. FUZZY EVALUATION MATRIX FOR ALTERNATIVES

Load	**LIF**	**VED**	**VSI**
Load 3	VH	MH	VH
Load 4	H	VH	MH
Load 5	VL	M	VH
Load 7	M	VH	VH
Load 9	L	VH	H
Load 10	VL	MH	VH
Load 12	ML	H	VH
Load 13	MH	VH	VH

The fuzzy evaluation matrix is constructed for both alternatives and criteria, as shown in Tables II and III. After the criteria have been evaluated by the decision-makers, the assessments of the criterion weights are aggregated into a single representative value using (2). Based on the TFNs defined in Table I, the fuzzy decision matrix is then established using (3). This is achieved by mapping the linguistic variables to their corresponding TFNs and organizing the resulting values into a structured matrix.

TABLE III. FUZZY EVALUATION MATRIX FOR CRITERIA

Criteria	**DM1**	**DM2**	**DM3**
LIF	MH	MH	H
VED	L	ML	ML
VSI	ML	M	M

TABLE IV. FUZZY DECISION MATRIX

Load	**LIF (0.57, 0.77, 0.93)**	**VED (0.07, 0.23, 0.43)**	**VSI (0.23, 0.43, 0.63)**
Load 3	(9, 10, 10)	(5, 7, 9)	(9, 10, 10)
Load 4	(7, 9, 10)	(9, 10, 10)	(5, 7, 9)
Load 5	(0, 0, 1)	(3, 5, 7)	(9, 10, 10)
Load 7	(3, 5, 7)	(9, 10, 10)	(9, 10, 10)
Load 9	(0, 1, 3)	(9, 10, 10)	(7, 9, 10)
Load 10	(0, 0, 1)	(5, 7, 9)	(9, 10, 10)
Load 12	(1, 3, 5)	(7, 9, 10)	(9, 10, 10)
Load 13	(5, 7, 9)	(9, 10, 10)	(9, 10, 10)

Subsequently, the normalized fuzzy decision matrix is obtained as depicted in Table V. The values in this matrix are computed by applying (5-7).

TABLE V. THE NORMALIZED FUZZY DECISION MATRIX

Load	**LIF (0.57, 0.77, 0.93)**	**VED (0.07, 0.23, 0.43)**	**VSI (0.23, 0.43, 0.63)**
Load 3	(0.32, 0.35, 0.35)	(0.12, 0.17, 0.22)	(0.20, 0.22, 0.22)
Load 4	(0.25, 0.32, 0.35)	(0.22, 0.24, 0.24)	(0.11, 0.15, 0.20)
Load 5	(0.00, 0.00, 0.04)	(0.07, 0.12, 0.17)	(0.20, 0.22, 0.22)
Load 7	(0.11, 0.18, 0.25)	(0.22, 0.24, 0.24)	(0.20, 0.22, 0.22)
Load 9	(0.00, 0.04, 0.11)	(0.22, 0.24, 0.24)	(0.15, 0.20, 0.22)
Load 10	(0.00, 0.00, 0.04)	(0.12, 0.17, 0.22)	(0.20, 0.22, 0.22)
Load 12	(0.04, 0.11, 0.18)	(0.17, 0.22, 0.24)	(0.20, 0.22, 0.22)
Load 13	(0.18, 0.25, 0.32)	(0.22, 0.24, 0.24)	(0.20, 0.22, 0.22)

After obtaining the weights from Table IV, (8) is applied to derive the normalized weights of the fuzzy decision matrix, which are presented in Table VI.

TABLE VI. THE NORMALIZED WEIGHTS OF THE FUZZY DECISION

Load	**LIF**	**VED**	**VSI**
Load 3	(0.18, 0.27, 0.33)	(0.01, 0.04, 0.09)	(0.05, 0.10, 0.14)
Load 4	(0.14, 0.24, 0.33)	(0.01, 0.06, 0.10)	(0.03, 0.07, 0.13)
Load 5	(0.00, 0.00, 0.03)	(0.00, 0.03, 0.07)	(0.05, 0.10, 0.14)
Load 7	(0.06, 0.14, 0.23)	(0.01, 0.06, 0.10)	(0.05, 0.10, 0.14)
Load 9	(0.00, 0.03, 0.10)	(0.01, 0.06, 0.10)	(0.04, 0.09, 0.14)
Load 10	(0.00, 0.00, 0.03)	(0.01, 0.04, 0.09)	(0.05, 0.10, 0.14)
Load 12	(0.02, 0.08, 0.17)	(0.01, 0.05, 0.10)	(0.05, 0.10, 0.14)
Load 13	(0.10, 0.19, 0.30)	(0.01, 0.06, 0.10)	(0.05, 0.10, 0.14)

Next, the overall values of the benefit and cost criteria for each alternative are computed in Table VII. In this study, only the benefit criteria are considered, while the cost criteria are excluded. Therefore, any calculations related to the cost criteria are omitted, and their values are set to zero. The SI for each alternative is determined by using (11). The alternative with the highest SI is prioritized in descending order. These values are summarized in Table VII.

TABLE VII. THE OVERALL PERFORMANCE INDEX

Load	$\mathbf{S_i^+}$	**SI**	**Rank**
Load 3	(0.23, 0.41, 0.56)	0.423	1
Load 4	(0.18, 0.37, 0.56)	0.400	2
Load 5	(0.05, 0.12, 0.24)	0.161	8
Load 7	(0.12, 0.29, 0.47)	0.328	4
Load 9	(0.05, 0.17, 0.34)	0.222	6
Load 10	(0.05, 0.13, 0.27)	0.175	7
Load 12	(0.08, 0.23, 0.41)	0.273	5
Load 13	(0.16, 0.34, 0.54)	0.381	3

Table VII presents the SI and the final ranking of each load based on the Fuzzy MOORA method. The SI values are calculated using the vertex method (11), which aggregates the normalized fuzzy values and the corresponding criteria weights. The loads with lower SI values receive lower rankings and are prioritized for curtailment to maintain the system stability.

Based on the ranking results, the LS priority order is established, where the lower-ranked loads with the lower SI values are shed first. This prioritization is used in simulation scenarios within the power grid and is compared, regarding flexibility and efficiency, with alternative methods discussed in the study.

In the test case, two diesel generators located on buses 2 and 8 adjust their output in response to the frequency deviations. When the system operates in island mode, as described in [6], the resulting frequency deviation is calculated as $\Delta f_1 = -1.4033$ Hz.

Thus, in the event of a fault while operating in island mode, the Microgrid frequency will drop by 1.4033 Hz. After the Primary and Secondary control processes, the frequency remains outside the allowable range, necessitating the LS procedure. The minimum required shedding power is calculated as $P_{shed,total}$=2.1788 MW.

The LS power is allocated according to the ranking results of the loads, using their respective Si values. The final shedding power distribution is computed using (12), and the results are presented in Table VIII.

TABLE VIII. THE LS PRIORITY PER BUS

Load	$\mathbf{P_{shed}}$ **(MW)**	$\mathbf{C_{penalty}}$ **($)**
Load 3	0.168	478.84
Load 4	0.178	456.55
Load 5	0.442	751.14
Load 7	0.217	510.06
Load 9	0.320	624.25
Load 10	0.407	761.43
Load 12	0.260	554.05
Load 13	0.187	515.63
Total	2.179	4,651.94

The LS results derived from Fuzzy MOORA-based rankings show that the highly critical loads experience less curtailment than the lower-priority ones, minimizing the economic impact while maintaining the technical and operational requirements. To evaluate its effectiveness, the proposed method is compared with AHP [6] and TOPSIS [15], focusing on the uncertainty handling, computational efficiency, adaptability, and economic impact. Compared to AHP and Fuzzy TOPSIS, Fuzzy MOORA offers a more efficient and adaptive solution for LS in microgrids [16-18]. AHP and Fuzzy TOPSIS involve extensive pairwise comparisons and complex distance calculations, which can hinder real-time deployment in large-scale systems. In contrast, Fuzzy MOORA's direct ranking mechanism ensures faster computation, making it more practical for dynamic microgrid operations.

Based on the ranking results obtained from the three MCDM methods, the corresponding LS allocation is summarized in Table IX. The results demonstrate that the proposed Fuzzy MOORA method achieves the most economically efficient LS strategy. This is attributed to its balanced distribution of the shedding power across all buses, ensuring that the critical loads experience minimal power reduction while maintaining the overall system stability. In contrast, Fuzzy TOPSIS exhibits lower economic efficiency, as the shedding power is distributed more uniformly across all buses, with smaller differences in the shedding levels between the high-importance and low-importance loads. This leads to a higher overall power curtailment, increasing the penalty costs and operational inefficiencies.

TABLE IX. LS ALLOCATION AND COST COMPARISON

Load	AHP			Fuzzy TOPSIS			Fuzzy MOORA		
	P_{shed}	Cost	Rank	P_{shed}	Cost	Rank	P_{shed}	Cost	Rank
Load 3	0.11569	329.7165	1	0.183	521.550	1	0.168	478.84	1
Load 4	0.19424	499.1968	2	0.199	511.430	2	0.178	456.55	2
Load 5	0.40698	691.866	8	0.406	690.200	8	0.442	751.14	8
Load 7	0.25365	596.0775	4	0.229	538.150	4	0.217	510.06	4
Load 9	0.33119	645.8205	6	0.316	616.200	6	0.320	624.25	6
Load 10	0.39415	737.0605	7	0.374	699.380	7	0.407	761.43	7
Load 12	0.27627	588.4551	5	0.267	568.710	5	0.260	554.05	5
Load 13	0.20664	570.3264	3	0.204	563.040	3	0.187	515.63	3
Total	2.179	4658.519		2.179	4708.660		2.179	4651.944	

TABLE X. SENSITIVITY OF AHP WEIGHTS TO CHANGES IN PAIRWISE COMPARISONS

Before modification				After modification			
Criteria	*LIF*	*VED*	*VSI*	Criteria	*LIF*	*VED*	*VSI*
LIF	1	3	2	LIF	1	3	3
VED	1/3	1	1/2	VED	1/3	1	1/2
VSI	1/2	2	1	VSI	1/3	2	1
Weight	0.539	0.164	0.297	Weight	0.594	0.157	0.249

TABLE XI. THE COMPARATIVE SUMMARY OF THE THREE MCDM METHODS

Criteria	AHP	Fuzzy TOPSIS	Fuzzy MOORA
Uncertainty handling	No fuzzy integration, assumes crip values based on 9-scaling method	Uses fuzzy numbers	Uses fuzzy logic with linguistic variables
Computational complexity	High, requires extensive pairwise comparisons	Moderate, involves multiple distance calculations	Low, follows a simple ranking process
Adaptability to dynamic changes	Poor, designed for static decision-making, time-consuming due to iterative calculations	Moderate adaptability but computationally heavier, computationally intensive for large-scale applications	High, dynamically adjusts load rankings, lightweight computations enable real-time decision-making

Fuzzy MOORA offers strong uncertainty-handling capabilities, which is a key advantage over traditional methods, such as AHP that rely on precise judgments and are sensitive to small input variations. By employing TFNs, Fuzzy MOORA effectively models the ambiguity in criteria, such as LIF, VED, and VSI. Although Fuzzy TOPSIS also incorporates fuzzy logic, it requires more complex calculations, including the computation of fuzzy distances to ideal and anti-ideal solutions, making it computationally more intensive, as portrayed in Table XI.

For instance, if the LIF is assessed as a confidence interval (e.g., 0.6–0.8) rather than a single crisp value (e.g., 0.7), Fuzzy MOORA can directly accommodate this through fuzzy representation. As displayed in Table X, changing DM2's evaluation of LIF from "High" to "Very High" alters the average fuzzy weight only slightly from (0.633, 0.833, 0.966) to (0.7, 0.867, 0.967) with the defuzzied value increasing marginally from 0.81 to 0.84. Since the other criteria remain unchanged, the load priority rankings are largely unaffected, demonstrating the method's robustness to subjective variation.

V. CONCLUSION

This study presents a Fuzzy Multi-Objective Optimization by Ratio Analysis under a Fuzzy Environment (MOORA)-based Multi-Criteria Decision-Making (MCDM) approach for optimal load ranking and shedding in microgrid systems. Unlike traditional Load Shedding (LS) techniques that rely on fixed frequency thresholds or predefined priority rules, the proposed method dynamically prioritizes the loads while balancing the technical stability and economic efficiency. By integrating fuzzy logic into the MOORA framework, the methodology addresses the uncertainty and imprecision, resulting in a more flexible and adaptive decision-making process.

Applied to a 16-bus microgrid model, the proposed method demonstrates superior performance by minimizing the economic losses and maintaining the system stability. The LS allocation results show that the critical loads experience less curtailment than non-essential ones, ensuring fair and optimal power distribution. The approach reduces the unnecessary disruptions, particularly for high priority loads often overlooked in conventional strategies.

In addition, the Fuzzy MOORA method offers high computational efficiency and structural simplicity, making it suitable for real-time applications in microgrids. Its ability to manage the uncertainty, adaptively rank the alternatives, and computing results rapidly establishes it as a robust solution for intelligent load management. Although their implementation requires domain-specific knowledge in power systems and fuzzy logic, the proper use of the weighting and ranking process ensures reliable outcomes.

Overall, the proposed approach provides a scalable and practical framework for diverse microgrid configurations. By combining uncertainty handling with computational agility, the

Fuzzy MOORA-based strategy enhances both the resilience and economic sustainability of modern smart grids.

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