An FBWM-TOPSIS Approach to Identify Critical Feeders for Reliability Centered Maintenance in Power Distribution Systems

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***Abstract*—With the limited availability of resources and time in the power industry, condition-based maintenance schemes are deemed effective to maintain the system desirable performance at all times. In this context, reliability centered maintenance is the key to strategically manage the assets in power grids enforcing the performance metrics to be the system reliability indicators. To this end and to most effectively allocate the maintenance time and resources, the most critical components in the grid, i.e., those needing maintenance the most with massive failure consequences, should be first identified. This article proposes a new multicriteria decision-making scheme to identify critical feeders in power distribution systems. Unlike the previous efforts which have focused on techniques based on the analytical hierarchical process, a best-worst method is employed in this article to prioritize the system reliability criteria based on the experts' knowledge and judgments. The proposed approach can achieve a faster and more accurate outcome in prioritizing the system criteria for maintenance. In addition, fuzzy theory is utilized to address the prevailing uncertainties in the experts' judgments and decisions. Finally, TOPSIS technique is employed to prioritize distribution feeders for future inspection and maintenance allocation.**

***Index Terms*—Best-worst method (BWM), critical feeders, multicriteria decision-making (MCDM), power distribution system, reliability centered maintenance (RCM).**

I. Introduction

RECENT reports have revealed that many large companies lose between 2% and 16% of their annual profits due to the system downtime [1]. Maintenance strategies, if effectively planned and timely performed, can enhance the system reliability performance and prevent loss of turnover by reducing the frequency and duration of system failures. Finding the best maintenance strategy in the system has long been a challenging concern. Reliability centered maintenance (RCM) has been found an effective approach to manage the maintenance priorities on some critical components, thereby characterizing a trade-off between preventive and corrective maintenance actions with the focus on the reliability measures [2]. RCM potentially results in higher reliability, quality, profitability, and productivity of the system with reduced downtime [3].

Most failures in power grids occur in the distribution sector [4], where effective maintenance planning and scheduling can significantly enhance system reliability and increase social welfare. An RCM architecture for implementation in power distribution systems can include three main stages [5], [6]. The *first stage* is to identify and prioritize the system critical feeders based on specific criteria. The *second stage* is to inspect the critical feeders, identify the possible failure modes, and conduct an analysis of their effects on the system performance. Clearly, those failure modes with higher impacts on the components and system performance should be prioritized for maintenance attention [7]. Finally, the *third stage* is to select the most effective and economically attractive maintenance strategy via a cost-benefit analysis.

Focusing primarily on the first stage, identifying the most critical components in the system can recast as a decision-making problem, which can be quantitatively or qualitatively approached. Quantitative methods include mathematical representation of the system model, complex evaluations, and investigation of the impacts of all components failures on the system operation and performance [8]–[13]. Quantitative methods, however, may not be applicable to systems for which the models are either extremely complex or are not completely available [14]. Additionally, experts' knowledge and opinions are typically neglected in the quantitative assessments. On the other hand, qualitative methods have been presented that can effectively capture the experts' knowledge and experiences in a simple and understandable manner [15]. Hybrid qualitative–quantitative methods have been also proposed in the literature for decision-making on the available alternatives based on various criteria [8]. Multicriteria decision-making (MCDM) is found as the most effective decision-making paradigm, which assists experts and decision-makers to select the most critical alternatives based on both quantitative and qualitative analyses [16].

Different classes of MCDM methods have been proposed in the literature applied to problems in various domains. For instance, the analytic hierarchy process (AHP) method was used to evaluate building refurbishment in [17]; the integrated fuzzy AHP (FAHP)-TOPSIS was applied for water loss management in [18]; the analytic network process method was employed for selecting sustainable suppliers in [19]; and the integrated

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best-worst method (BWM) and VIKOR technique were presented for prioritizing the airports in [20]. In power systems, however, the application of MCDM methods has been observed less focused, particularly in the development and implementation of the RCM plans. For instance, a framework based on the theoretical reliability models integrated with the practical AHP method was employed in [21] to identify the critical components in power transmission systems for RCM implementation. In [22], the DEMATEL method was employed to identify the optimal electric vehicle stations by taking advantage of grey theory to cope with the decision ambiguity. The uncertainty in experts' judgment when conducting the pairwise comparisons was also addressed by the fuzzy theory in two different problems: identification of critical components in power distribution systems using FAHP [6] and evaluating the risk of the electric vehicle charging infrastructure through fuzzy TOPSIS technique [23]. Overall, the AHP method was employed in the past literature to identify the system critical components for RCM implementation in power systems. The BWM approach, newly proposed in [24]–[26], can effectively offer higher accuracy in pairwise comparisons in a shorter timeframe. This is achieved due to the lower number of requisite pairwise comparisons between criteria and an appropriate consistency ratio (CR) [24].

This article proposes a BWM-TOPSIS framework to identify the critical feeders in power distribution systems. Criticality is evaluated based on the reliability criteria, i.e., system average interruption frequency index (SAIFI), system average interruption duration index (SAIDI), energy not supplied (ENS), and the customer interruption cost (CIC). To this end, the reliability criteria are first prioritized by the system decision-maker. The feeders are then ranked with respect to the reliability weights. In doing so, opinions of experts are sought in pairwise comparisons. Unlike previous studies, this article proposes a BWM approach to prioritize the system criteria. In addition, fuzzy BWM (FBWM) is employed to capture the uncertainties in the pairwise comparisons between criteria, and the results are compared with the conventional BWM. Finally, the weights are utilized to prioritize distribution feeders through the TOPSIS approach, and sensitivity analysis is performed to verify the robustness of the analytics. The feeder prioritization results are compared with AHP and FAHP methods to demonstrate the validity and effectiveness of the proposed framework.

The rest of this article is structured as follows. In Section II, the applications of BWM, FBWM, and TOPSIS methods are presented. Section III is devoted to case studies and the numerical evaluations of the proposed methods. Sensitivity analysis is presented in Section IV. Conclusions are eventually drawn in Section V.

II. Proposed Approach to Critical Feeder Identification

MCDM methods are employed in this article to identify the critical feeders in power distribution systems. MCDM techniques provide a platform for decision-makers to apply their knowledge and experience in order to choose the optimal alternatives with respect to specific criteria. Accordingly, a critical task for the decision-makers is to perform precise pairwise comparisons between a series of decision criteria [16]. As shown in Fig. 1, the BWM technique is applied in this article to achieve the optimal weights for system criteria according to the pairwise comparisons received from the electric utility experts. Accordingly, the feeders are prioritized through the TOPSIS technique [27]–[30]. Details of the proposed approach are described in the following.

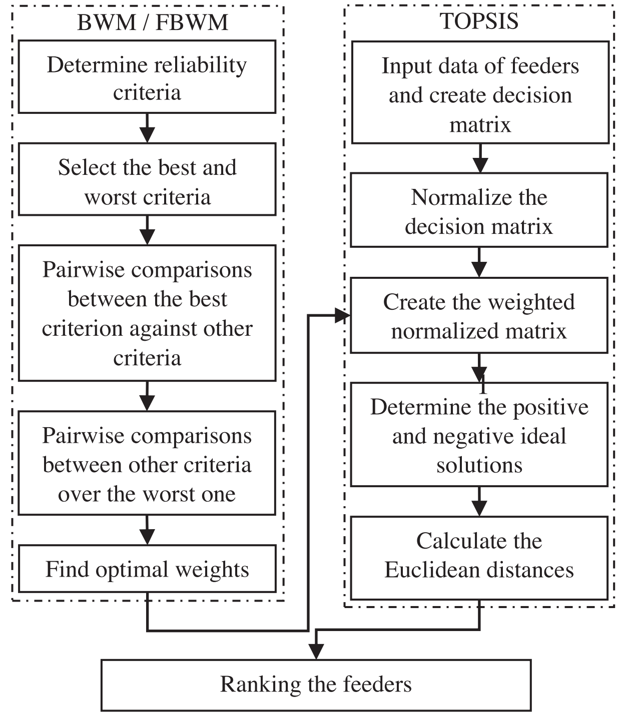

Fig. 1. Flowchart of the proposed feeder prioritization approach.

TABLE I
Linguistic Table for Pairwise Comparisons

Degree of Importance	Definition
1	Equally Important
3	Moderately Important
5	Strongly Important
7	Very Strongly Important
9	Extremely Important
2, 4, 6, 8	Comparison among above categories

A. BWM

The BWM method, developed for the first time by J. Rezaei, in 2015, is the latest MCDM technique and is founded based on pairwise comparisons. The experts should implement pairwise comparisons between the decision criteria based on their experiences and opinions according to the linguistic table shown in Table I. In general, the implementation of the BWM method includes five main steps as follows [24]–[26].

Step 1. Definition of the criteria for feeder prioritization.

A set of criteria $c = \{c_1, c_2, \ldots, c_n\}$ is determined for decision-making. The criteria can be the system reliability indices such as $\{$SAIFI (c_1), SAIDI (c_2), ENS (c_3), and CIC $(c_4)\}$.

Step 2. Selecting the best (most important) criterion and the worst (least important) criterion by each expert.

Step 3. Pairwise comparisons of the best criterion with respect to the other criteria.

Each expert performs pairwise comparisons based on the Saaty scale [31] shown in Table I. The achieved vector would be $A_B = (a_{B1}, \ldots, a_{Bn})$, where a_{Bj} demonstrates the privilege of the best criterion against the other criteria.

Step 4. Pairwise comparisons of the other criteria and the worst criterion.

Each expert compares all criteria against the worst criterion according to the linguistic Table I. The obtained vector can be $A_W = (a_{1W}, \ldots, a_{nW})^T$, where a_{jW} shows the merits of the other criteria against the worst criterion.

Step 5. Assessment of the optimal weights for the criteria.

The weights of the decision criteria are assessed based on the following nonlinear optimization procedure [24]:

$$\begin{cases} \min\max_j \left\{ \left| \frac{w_B}{w_j} - a_{Bj} \right|, \left| \frac{w_j}{w_W} - a_{jW} \right| \right\} \\ \text{S.t.} \\ \sum_j w_j = 1 \\ w_j \geq 0, \text{for all } j = 1, 2, \ldots, n. \end{cases} \tag{1}$$

According to (1), the maximum absolute difference between the weight ratios and the number of pairwise comparisons should be minimized. Equation (1) can also be rewritten as follows:

$$\begin{cases} \min \xi \\ \text{S.t.} \\ \left| \frac{w_B}{w_j} - a_{Bj} \right| \leq \xi, \text{for all } j \\ \left| \frac{w_j}{w_W} - a_{jW} \right| \leq \xi, \text{for all } j \\ \sum_j w_j = 1 \\ w_j \geq 0, \text{for all } j = 1, 2, \ldots, n. \end{cases} \tag{2}$$

In some cases, particularly when the number of criteria is more than three, the multioptimality solution is a challenge. Hence, the above nonlinear equation can be linearized [25] to achieve a single optimal solution as follows:

$$\begin{cases} \min \xi^L \\ \text{S.t.} \\ \left| w_B - a_{Bj} w_j \right| \leq \xi^L, \text{for all } j \\ \left| w_j - a_{jW} w_W \right| \leq \xi^L, \text{for all } j \\ \sum_j w_j = 1 \\ w_j \geq 0, \text{for all } j = 1, 2, \ldots, n. \end{cases} \tag{3}$$

By solving the above problems, the optimal weights$(w_1^*,\ w_2^*,\ \ldots,\ w_n^*)$ for decision criteria are obtained.

B. Fuzzy BWM

In some cases, experts and decision-makers cannot overcome vagueness, subjectiveness, and uncertainty when conducting the pairwise comparisons. Therefore, the FBWM method is used to eliminate the ambiguity and enhance the accuracy. The major difference between the BWM and FBWM is in using fuzzy numbers for pairwise comparisons. Each triangular fuzzy number (*l*, *m*, *u*) includes lower-bound (*l*), middle-bound (*m*), and upper-bound (*u*). Hence, Table II can be used to cover a wider range of experts' insight for pairwise comparisons. The membership function of the triangular fuzzy numbers is displayed as follows [32]:

TABLE II
TRIANGULAR FUZZY SCALE FOR PAIRWISE COMPARISONS

Degree of Importance	Definition
(1, 1, 1)	Equally Important
(1, 3/2, 2)	Moderately Important
(2, 5/2, 3)	Strongly Important
(3, 7/2, 4)	Very Strongly Important
(9/2, 9/2, 9/2)	Extremely Important
(2/3, 1, 3/2), (3/2, 2, 5/2), (5/2, 3, 7/2), (7/2, 4, 9/2)	Comparison among above categories

$$\mu_N(x) = \begin{cases} \frac{x-l}{m-l}, & l \leq x \leq m \\ \frac{u-x}{u-m}, & m \leq x \leq u \\ 0, & \text{otherwise.} \end{cases} \tag{4}$$

1) Fuzzy Rules Definition: If $A = (l_1,\ m_1,\ u_1)$ and $B = (l_2,\ m_2,\ u_2)$ are two triangular fuzzy numbers, the fuzzy arithmetic operators are [32]

Addition:

$$A \oplus B = (l_1 + l_2, m_1 + m_2, u_1 + u_2). \tag{5}$$

Subtraction:

$$A \ominus B = (l_1 - u_2, m_1 - m_2, u_1 - l_2). \tag{6}$$

Multiplication:

$$A \otimes B = (l_1 l_2, m_1 m_2, u_1 u_2). \tag{7}$$

Inverse:

$$A^{-1} = \left(\frac{1}{u_1}, \frac{1}{m_1}, \frac{1}{l_1} \right). \tag{8}$$

Equation (2) is fuzzified in line with [26] as follows:

$$\begin{cases} \min \tilde{\xi}^* \\ \text{S.t.} \\ \tilde{\xi}^* = (k^*, k^*, k^*) \\ \left| \frac{(l_B^w, m_B^w, u_B^w)}{(l_j^w, m_j^w, u_j^w)} - (l_{Bj}, m_{Bj}, u_{Bj}) \right| \leq (k^*, k^*, k^*) \\ \left| \frac{(l_j^w, m_j^w, u_j^w)}{(l_W^w, m_W^w, u_W^w)} - (l_{jW}, m_{jW}, u_{jW}) \right| \leq (k^*, k^*, k^*) \\ \sum_{j=1}^n R(\tilde{w}_j) = 1 \\ l_j^w \leq m_j^w \leq u_j^w \\ l_j^w \geq 0 \\ j = 1, 2, \ldots, n. \end{cases} \tag{9}$$

The solution to (9) will result in the optimal fuzzy weights$(\tilde{w}_1^*,\ \tilde{w}_2^*,\ \ldots,\ \tilde{w}_n^*)$, where $\tilde{w}_n^*$ are fuzzy weights. Equation (10) is used to convert the fuzzy weights into crisp weights(w_n^*). The crisp weight is obtained by the following equation, which is the graded mean integration representation of the fuzzy weights [26]

$$R(\tilde{w}_j) = \frac{(l_j + 4m_j + u_j)}{6} \quad \text{for } j = 1, 2, \ldots, n. \tag{10}$$

TABLE III
VALUES OF THE CONSISTENCY INDEX BASED ON EACH FUZZY NUMBER FOR FBWM

a_{BW}	CI	a_{BW}	CI	a_{BW}	CI
(1, 1, 1)	3	(3/2, 2, 5/2)	5.29	(3, 7/2, 4)	7.37
(2/3, 1, 3/2)	3.8	(2, 5/2, 3)	6	(7/2, 4, 9/2)	8.04
(1, 3/2, 2)	4.56	(5/2, 3, 7/2)	6.69	(9/2, 9/2, 9/2)	8.04

2) Consistency Ratio Definition: Varying in a range between 0 and 1, CR represents the reliability of the achieved weights. A zero value for CR corresponds to completely reliable weights, while a CR $= 1$ shows the full inconsistency in the pairwise comparisons. Rezaei [24] and Sen and Haoran [26] demonstrated that the CR metric should be assessed for nonlinear and FBWM, while ξ^l in (3) directly reflects the value of CR for linear types [25]. As the linear BWM is employed here in the case studies, only the procedure to assess the CR in the fuzzy problem is described. The pairwise comparison is fully consistent if $\tilde{a}_{Bj} \times \tilde{a}_{jW} = \tilde{a}_{BW}$; otherwise, an inconsistency will be reported. Hence, when both $\tilde{a}_{Bj}$ and $\tilde{a}_{jW}$ are equal to $\tilde{a}_{BW}$, the greatest inconsistency is resulted. Consistency index (CI) for FBWM is assessed by solving (11) [26]

$$(CI)^2 - (1 + 2u_{BW}) \times CI + \left(u_{BW}^2 - u_{BW}\right) = 0 \quad (11)$$

where u_{BW} is the upper bound of the maximum $\tilde{a}_{BW} = (l_{BW}, m_{BW}, u_{BW})$, which is used in the pairwise comparisons. CI is assessed based on (11), and the results are illustrated in Table III for each fuzzy number. Finally, the CR index is calculated by

$$\mathrm{CR} = \frac{\xi^*}{\mathrm{CI}} \quad (12)$$

where ξ^* is the crisp value of $\tilde{\xi}^* = (k^*, k^*, k^*)$ which is found by solving the optimization (9).

C. Topsis

The TOPSIS technique is an MCDM approach that is used for prioritizing the distribution feeders with respect to the given criteria. A decision matrix is defined here as presented in (13)

$$\begin{array}{cc} \begin{array}{c} a_1 \\ \vdots \\ a_m \end{array} & \begin{pmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{pmatrix} \\ & \begin{array}{ccc} c_1 & \cdots & c_n \end{array} \end{array} \quad (13)$$

where $\{a_1, \ldots, a_m\}$ is a set of feeders and $\{c_1, \ldots, c_n\}$ is a set of criteria; x_{ij} shows the score corresponding to feeder *i* with respect to criterion *j*. The TOPSIS technique consists of six steps [27]–[30] that are summarized as follows.

Step 1. Organize the decision matrix.

Step 2. Normalize the decision matrix through (14).

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \text{with } i = 1, \ldots, m \text{ and } j = 1, \ldots, n \quad (14)$$

Step 3. Establish the weighted normalized decision matrix by multiplying the weights obtained from BWM or FBWM by normalized matrix achieved in Step 2.

$$p_{ij} = w_j \times r_{ij} \quad (15)$$

Step 4. Determine the positive and negative ideal solutions. The type of criteria should be specified first and the ideal solution is then determined. While the benefit criterion (J_1) refers to those that experts are eager to enhance (e.g., quality), cost criterion (J_2) refers to those criteria that the experts are eager to decline (e.g., cost). If p_j^+ and p_j^- are, respectively, positive and negative ideal solutions, therefore

$$p_j^+ = (\max p_{ij} \text{ if } j \in J_1;\ \min p_{ij} \text{ if } j \in J_2) \quad (16)$$

$$p_j^- = (\min p_{ij} \text{ if } j \in J_1;\ \max p_{ij} \text{ if } j \in J_2). \quad (17)$$

Step 5. Evaluate the Euclidean distances as follows:

$$\begin{cases} S_i^+ = \left(\sum \left(p_{ij} - p_j^+\right)^2\right)^{0.5} \\ S_i^- = \left(\sum \left(p_{ij} - p_j^-\right)^2\right)^{0.5} \end{cases} \quad (18)$$

where S_i^+ is the distance of feeders from the positive ideal solution, and S_i^- is that from the negative ideal solution. Hence, the feeder with the shortest distance from the positive ideal and the longest from the negative ideal will have the best qualification. In order to determine the critical feeders, the process is reversed.

Step 6. Evaluate the relative closeness for each feeder to the ideal solution and prioritize them based on (19)

$$d_i = \frac{S_i^-}{S_i^+ + S_i^-}. \quad (19)$$

In this step, the value of closeness to the positive ideal solution is measured. The highest value of d_i corresponds to the feeder with the best condition, while the lowest value is associated with the most critical feeder which initially requires inspection. Thus, the criticality list is derived by sorting the feeders from the lower to higher d_i values.

III. Real Case Study

In this section, the presented methods are applied to a real power distribution system in order to determine the critical feeders for maintenance. As shown in Fig. 1, the weights for criteria are first assessed through BWM and FBWM; the results are next compared through the CR index; and finally, the more accurate weights are used to sort 20 feeders through an application of the TOPSIS technique.

A. Weight Evaluation for Decision Criteria

Here, the results derived from the fuzzy and conventional BWM methods are compared, and the results with weights corresponding to lower CR are applied for sorting 20 feeders. The following four reliability criteria are considered to identify and prioritize the critical feeders [33].

1) SAIFI: One very commonly used reliability index in power distribution systems is the failure rate of the load points, indicating the number of failures in a given period of time. Accordingly, SAIFI can be assessed as a customer-oriented reliability index that indicates the average failure rates for each customer in a year. Increasing failure rates can reflect the deterioration level of a feeder. As a result, a higher SAIFI represents a more critical feeder

$$\mathrm{SAIFI} = \sum_{i=1}^{n} \lambda_i N_i \Bigg/ \sum_{i=1}^{n} N_i \tag{20}$$

where λ_i is the failure rate and N_i is the number of customers in load point *i*.

2) SAIDI: Outage duration is defined as the period of time the feeder has failed or load curtailment has occurred. SAIDI is a reliability indicator that indicates the average outage duration for each customer in a year. The longer outage duration will result in a higher SAIDI. Consequently, the feeder with a higher SAIDI is recognized as a more critical feeder for maintenance and resource allocation

$$\mathrm{SAIDI} = \sum_{i=1}^{n} U_i N_i \Bigg/ \sum_{i=1}^{n} N_i \tag{21}$$

where U_i is the annual outage time of load point *i*.

3) ENS: It is a reliability indicator that measures the amount of ENS (MWh) due to the failures or outages in a feeder. It is apparent that the ENS is derived from the outage duration and failure rate. As a result, a feeder with a higher ENS is found more critical for maintenance

$$\mathrm{ENS} = \sum_{i} L_i U_i \tag{22}$$

where L_i is the average demand at load point *i*.

4) CIC: It is a monetary indicator that represents the value of electricity that is not supplied due to the outages. The value of the electricity outage varies based on the type of customers (e.g., residential, commercial, and industrial). The feeder with a higher CIC is considered with higher priority for maintenance planning and scheduling

$$\mathrm{CIC} = \sum_{i} \mathrm{ENS}_i \times \mathrm{VOLL}_i \tag{23}$$

where ENS_i is the ENS (MWh/year) and VOLL_i (\$/MWh) is the value of lost load at load point *i*.

Pairwise comparisons are made between the criteria with respect to the views and experiences of six experts. The best and the worst criteria are determined by each expert. Tables IV and V, respectively, show the importance of the best criterion against other criteria and the importance of other criteria over the worst criterion from each expert's perspective. For instance, according to the viewpoint of expert 1, ENS is very strongly important compared to SAIFI, according to the definition presented in Table I. The linear BWM is applied, the results of which are derived in (3) and tabulated in Table VI. The results demonstrate that the ENS with a weight of 0.46 and CIC with a weight of 0.14 are, respectively, the most and the least important decision criteria.

TABLE IV
PAIRWISE COMPARISONS BETWEEN THE BEST CRITERION OVER OTHER CRITERIA

Expert no.	Best criteria	SAIFI	SAIDI	ENS	CIC
1	ENS	7	8	1	9
2	ENS	3	7	1	9
3	ENS	5	3	1	2
4	ENS	4	4	1	3
5	SAIFI	1	2	4	5
6	SAIDI	6	1	2	4

TABLE V
PAIRWISE COMPARISONS BETWEEN OTHER CRITERIA OVER THE WORST ONE

Expert no.	1	2	3	4	5	6
Worst criteria	CIC	CIC	SAIFI	SAIDI	CIC	SAIFI
SAIFI	1	7	1	2	5	1
SAIDI	2	4	3	1	2	6
ENS	9	9	5	4	3	4
CIC	1	1	4	3	1	3

Application of BWM method has three main advantages over the other state-of-the-art weight assessment methods such as AHP. Fewer numbers of pairwise comparisons, higher consistency, and the use of integer numbers solely for making easier comparisons are the main advantages, which have been verified in [24]. While $2n-3$ number of pairwise comparisons are required in BWM, a total of $n(n-1)/2$ comparisons are performed in AHP, where *n* is the number of criteria. This reduction in the number of comparisons, especially when the number of criteria is high, leads to a more consistent CR in BWM than AHP [24]. In order to illustrate the advantages of BWM against the AHP method, our experts are asked to make pairwise comparisons between the criteria based on the AHP method. Table VII shows the pairwise comparisons for the third expert according to the AHP method, where the corresponding CR is found 0.2. However, the CR of 0.2 violates the desired threshold of 0.1 resulting in a compromised outcome with less accuracy [31]. This indicates that the obtained results by AHP application are not reliable in our case, and comparisons should be revised which need more time and more experts' collaboration. Table VI shows that the CR of the third expert is found 0.065 when the BWM method is applied, which indicates a more reliable outcome in our studied application.

FBWM is applied to capture the uncertainties within the pairwise comparisons. The Fuzzy numbers cover a larger scope of experts' viewpoints. Therefore, it can lead to more accurate weights. Fuzzification is applied to each expert's numbers based on Table II. The fuzzy pairwise comparisons are demonstrated in Tables VIII and IX. Table VIII shows the fuzzy pairwise comparisons between the best criterion over the other criteria. Similarly, Table IX shows the fuzzy pairwise comparisons between other criteria over the worst one. Table X indicates the obtained weights based on the insights from each expert. Table XI shows the final mean weights obtained by FBWM, where the ENS with a weight of 0.371 and CIC with a weight of 0.187 are, respectively, rated as the best and worst criteria by

TABLE VI
WEIGHT OF CRITERIA OBTAINED BY APPLYING THE LINEAR BWM

Criteria	**Mean weight**	Expert 1	Expert 2	Expert 3	Expert 4	Expert 5	Expert 6
SAIFI	0.19	0.09	0.242	0.081	0.158	0.507	0.0714
SAIDI	0.21	0.1	0.104	0.179	0.1052	0.2603	0.5
ENS	0.46	0.72	0.601	0.47	0.5263	0.1507	0.2857
CIC	0.14	0.09	0.053	0.27	0.2105	0.082	0.1429
ξ^l	0.0922	0.09	0.126	0.065	0.105	0.096	0.071

TABLE VII
PAIRWISE COMPARISON FOR THE THIRD EXPERT (AHP METHOD)

Expert 3	SAIFI	SAIDI	ENS	CIC
SAIFI	1	1/3	1/5	1/4
SAIDI	3	1	1/3	5
ENS	5	3	1	2
CIC	4	1/5	1/2	1

TABLE VIII
FUZZY PAIRWISE COMPARISONS BETWEEN THE BEST CRITERION OVER OTHER CRITERIA

Expert no.	**Best criteria**	SAIFI	SAIDI	ENS	CIC
1	ENS	(3, 7/2, 4)	(7/2, 4, 9/2)	(1, 1, 1)	(9/2, 9/2, 9/2)
2	ENS	(1, 3/2, 2)	(3, 7/2, 4)	(1, 1, 1)	(9/2, 9/2, 9/2)
3	ENS	(2, 5/2, 3)	(1, 3/2, 2)	(1, 1, 1)	(2/3, 1, 3/2)
4	ENS	(3/2, 2, 5/2)	(3/2, 2, 5/2)	(1, 1, 1)	(1, 3/2, 2)
5	SAIFI	(1, 1, 1)	(2/3, 1, 3/2)	(3/2, 2, 5/2)	(2, 5/2, 3)
6	SAIDI	(5/2, 3, 7/2)	(1, 1, 1)	(2/3, 1, 3/2)	(3/2, 2, 5/2)

TABLE IX
FUZZY PAIRWISE COMPARISONS BETWEEN OTHER CRITERIA OVER THE WORST ONE

Expert no.	1	2	3	4	5	6
Worst criteria	CIC	CIC	SAIFI	SAIDI	CIC	SAIFI
SAIFI	(1, 1, 1)	(3, 7/2, 4)	(1, 1, 1)	(2/3, 1, 3/2)	(2, 5/2, 3)	(1, 1, 1)
SAIDI	(2/3, 1, 3/2)	(3/2, 2, 5/2)	(1, 3/2, 2)	(1, 1, 1)	(2/3, 1, 3/2)	(5/2, 3, 7/2)
ENS	(9/2, 9/2, 9/2)	(9/2, 9/2, 9/2)	(2, 5/2, 3)	(3/2, 2, 5/2)	(1, 3/2, 2)	(3/2, 2, 5/2)
CIC	(1, 1, 1)	(1, 1, 1)	(3/2, 2, 5/2)	(1, 3/2, 2)	(1, 1, 1)	(1, 3/2, 2)

TABLE X
WEIGHT OF CRITERIA OBTAINED BY FBWM FOR EACH EXPERT

Criteria	**Expert 1**	**Crisp value**	**Expert 2**	**Crisp value**	**Expert 3**	**Crisp value**
SAIFI	(0.151, 0.161, 0.161)	0.16	(0.297, 0.3, 0.323)	0.303	(0.13, 0.146, 0.146)	0.143
SAIDI	(0.12, 0.154, 0.164)	0.15	(0.107, 0.153, 0.153)	0.145	(0.176, 0.237, 0.283)	0.234
ENS	(0.529, 0.572, 0.572)	0.565	(0.396, 0.472, 0.472)	0.46	(0.262, 0.335, 0.388)	0.332
CIC	(0.125, 0.125, 0.125)	0.125	(0.073, 0.096, 0.097)	0.092	(0.249, 0.299, 0.299)	0.291
$\tilde{\xi}^*$	(0.284, 0.284, 0.284)	0.284	(0.411, 0.411, 0.411)	0.411	(0.205, 0.205, 0.205)	0.205
	CR= 0.035		CR= 0.05		CR= 0.034	
Criteria	**Expert 4**	**Crisp value**	**Expert 5**	**Crisp value**	**Expert 6**	**Crisp value**
SAIFI	(0.193, 0.193, 0.229)	0.199	(0.354, 0.354, 0.427)	0.366	(0.128, 0.137, 0.14)	0.136
SAIDI	(0.193, 0.193, 0.194)	0.193	(0.246, 0.246, 0.246)	0.246	(0.317, 0.379, 0.418)	0.3752
ENS	(0.271, 0.323, 0.543)	0.351	(0.146, 0.211, 0.3)	0.215	(0.243, 0.306, 0.35)	0.3028
CIC	(0.132, 0.272, 0.323)	0.257	(0.127, 0.171, 0.226)	0.173	(0.173, 0.173, 0.248)	0.1855
$\tilde{\xi}^*$	(0.321, 0.321, 0.321)	0.321	(0.436, 0.436, 0.436)	0.436	(0.236, 0.236, 0.236)	0.236
	CR= 0.061		CR= 0.073		CR= 0.035	

all experts. Results derived from BWM and FBWM techniques demonstrate the CR of 0.0922 and 0.048, respectively. Hence, FBWM results in a lower CR, which indicates that the weights of criteria are more accurate and reliable. Therefore, the weights achieved from FBWM are employed to prioritize the critical feeders through the TOPSIS method in the following.

B. Feeders Ranking

In this section, the TOPSIS technique is utilized to determine and prioritize the critical feeders. The decision matrix including the information from 20 feeders based on the defined criteria is shown in Table XII. Weights derived from the FBWM technique are multiplied by the normalized decision matrix to establish

TABLE XI
FINAL MEAN WEIGHT OF CRITERIA DERIVED BY FBWM

Criteria	Mean weight
SAIFI	0.218
SAIDI	0.224
ENS	0.371
CIC	0.187
CR=0.048	

TABLE XII
DECISION MATRIX

Feeder no.	SAIFI	SAIDI	ENS	CIC
F1	0.4993	1.6234	1446.7	54974.6
F2	0.62291	0.31906	573	65322
F3	0.36139	0.27355	369.4	11082
F4	1	1.21591	1244.7	1867.05
F5	0.62872	0.23577	81.8	122.7
F6	1.52972	1.91175	2440	370880
F7	1.5103	1.8059	457.9	1373.7
F8	2.28283	3.7789	2944.5	4416.75
F9	0.68579	0.84904	1385.2	2077.8
F10	1.66678	0.94717	1226.8	12268
F11	2.13581	2.10161	2514.1	3771.15
F12	3.77134	3.09785	4825.4	7238.1
F13	0.41811	0.20906	185.7	5571
F14	0.96802	1.15795	1366.6	2049.9
F15	0.44022	0.17609	290.2	23216
F16	1.58895	1.20839	1091.9	32757
F17	0.70861	0.44285	220.1	330.15
F18	1.41904	1.06703	444	4440
F19	0.82385	0.67281	1107.1	1660.65
F20	2.2946	2.59359	2170.7	82486.6

TABLE XIII
WEIGHTED NORMALIZED MATRIX

Feeder no.	SAIFI	SAIDI	ENS	CIC
F1	0.016	0.0502	0.0685	0.0262
F2	0.02	0.0099	0.0271	0.0312
F3	0.0116	0.0085	0.0175	0.0053
F4	0.032	0.0376	0.059	0.00089
F5	0.0201	0.0073	0.0039	0.0000585
F6	0.049	0.0591	0.1156	0.1769
F7	0.0484	0.0558	0.0217	0.000655
F8	0.0731	0.1168	0.1395	0.0021
F9	0.022	0.0262	0.0656	0.000991
F10	0.0534	0.0293	0.0581	0.0059
F11	0.0684	0.0649	0.1191	0.0018
F12	0.1208	0.0957	0.2286	0.0035
F13	0.0134	0.0065	0.0088	0.0027
F14	0.031	0.0358	0.0647	0.000978
F15	0.0141	0.0054	0.0137	0.0111
F16	0.0509	0.0373	0.0517	0.0156
F17	0.0227	0.0137	0.0104	0.000157
F18	0.0455	0.033	0.021	0.0021
F19	0.0264	0.0208	0.0524	0.000792
F20	0.0735	0.0801	0.1028	0.0393

the weighted normalized matrix based on (15) as displayed in Table XIII. All the four criteria are considered as the cost criteria, since a higher value for such criteria results in lower system performance. In other words, the feeders with higher values of SAIFI, SAIDI, ENS, and CIC should be viewed as more critical feeders. According to (16) and (17), the minimum value in each column of the weighted normalized matrix is determined as p_j^+ and the maximum value of each column is determined as p_j^-. The Euclidean distances from the positive and negative ideal solutions for each feeder are assessed based on (18). The feeder with the least distance from the positive ideal and the longest distance from the negative ideal solution is selected as the best condition. Conversely, if the Euclidean distance of a feeder from the positive ideal is longer and from the negative ideal is shorter, that feeder will be more critical. Finally, feeders' prioritization is done in the light of (19). While the highest value of d_i corresponds to the feeder with the best condition, the lowest d_i is associated with the most critical feeder, which needs to be placed on the inspection and maintenance priority list. Therefore, critical feeders should be ranked from the lowest to the highest value of d_i, where the inspection should be started with the lowest in the list.

TABLE XIV
FEEDERS RANKING LIST: COMPARISONS OF BWM AND FBWM

Rank no.	FBWM		BWM	
	Feeder no.	Score	Feeder no.	Score
1	F12	0.39675	F12	0.30009
2	F6	0.39946	F6	0.447633
3	F8	0.520598	F8	0.462226
4	F20	0.576083	F11	0.553949
5	F11	0.607637	F20	0.557904
6	F1	0.752656	F1	0.732492
7	F10	0.784977	F14	0.763161
8	F16	0.785695	F10	0.769848
9	F14	0.79187	F9	0.772368
10	F4	0.802331	F4	0.778888
11	F9	0.806338	F16	0.779963
12	F7	0.81607	F19	0.817197
13	F19	0.842197	F7	0.830927
14	F18	0.862228	F18	0.872805
15	F2	0.878409	F2	0.888655
16	F17	0.953603	F3	0.948428
17	F15	0.954131	F15	0.956156
18	F3	0.954494	F17	0.956718
19	F5	0.973543	F5	0.977756
20	F13	0.981765	F13	0.980359

The prioritization of critical feeders for both FBWM and conventional BWM is shown in Table XIV. F12 is found the most critical with the highest ENS, SAIFI, and almost SAIDI indicators among other feeders for both fuzzy and conventional BWM. Therefore, it should be placed first in the inspection priority list. Similarly, F6 with a slightly different score occupies the second priority in the list of the critical feeders, while F13 receives the best conditions among all feeders for both FBMW and BWM. However, due to the difference weights assigned to the decision criteria when using FBWM and BWM, the feeder prioritization outcome is different for several feeders. For example, while F9 is placed in priority #11 by weight assessment through FBWM, it is located in position #9 in the case of BWM application. This is because the weights of criteria directly impact the priority of feeders. FBWM, which considers the uncertainty of judgments and has lower CR, is recognized as a more accurate weight assessment approach to achieve the optimal critical ranking list.

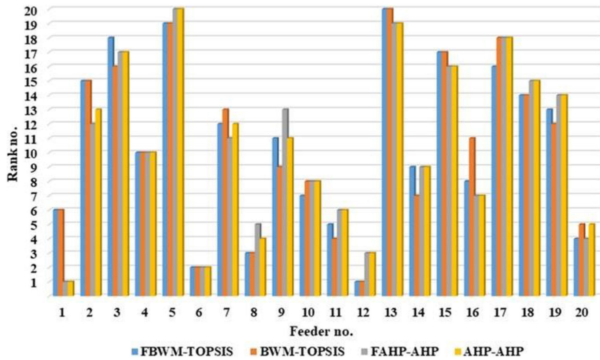

Fig. 2. Critical feeder ranking chart.

It is worthwhile to study the impacts of the criteria weights on the feeder prioritization outcome. For instance, if the same weights are assigned to all criteria, F7 will be found more critical than F14. However, the proposed optimal criteria weighting mechanism shows that F14 is more critical than F7, as presented in Table XIV. Fig. 2 shows a chart of the prioritized feeders based on the criticality values. Prioritization results are plotted according to the proposed scheme. On the contrary, weights of criteria are evaluated by AHP [31] and FAHP [34] methods and feeders are finally ranked by the AHP method. The chart clearly demonstrates that the criticality prioritization can change based on various weights derived from different methods. For instance, F12 is determined as the most critical feeder by FBWM and BWM, while F1 is manifested as the most critical feeder in FAHP and AHP framework. F13 is placed in the last priority by the proposed method, while it is settled with a slight difference in priority #19 when using the FAHP and AHP. F6 and F4 are the only feeders with the same ranking in all methods. The most changes in ranking results are between the proposed framework and the weight assessment through both fuzzy and conventional AHP. These ranking differences are primarily due to the following two reasons: first, differences in weight assessment methods mentioned in Section III-A and second, the discrepancies in ranking evaluation methods. The results confirm that the criteria weights play a key role in the final decision on the critical feeders. Thus, the FBWM method, which well captures and manages the uncertainty in the expert's judgments and features a smaller number of pairwise comparisons when compared against other methods, is recommended for deriving more accurate weights and, subsequently, finding the critical feeders more precisely. In terms of prioritization, the TOPSIS method results in more credible results than AHP. This is because TOPSIS considers the distances between the ideal solutions, while AHP only relies on pairwise comparisons and obtained weights.

IV. Sensitivity Analysis

Sensitivity analysis is here performed to investigate the robustness of the feeders' prioritization decisions with respect to variations in criteria weights in line with the presented studies in [7] and [35]. To this end, ENS weight is varied from 0.1 to 0.9 and weights of other criteria are also varied in proportion as shown in Table XV. Fig. 3 indicates the feeder ranking based on the variation of weights through the TOPSIS method. Results present that for an ENS weight higher than 0.3, F12 is found as the most critical feeder, and F13 and F5 are the least important ones. If ENS weight changes to lower than 0.3, F12 would rank second in the criticality list, and F13 would be the last. The priority of feeders such as F9 may change significantly with weights variations. Thus, the results indicate that feeders' prioritization is relatively sensitive to the weights of criteria and calls for mechanisms to accurately weigh the decision criteria.

TABLE XV
Criteria Weight Changes in Different Runs

Criteria	SAIFI	SAIDI	ENS	CIC
FBWM weights	0.218	0.224	0.371	0.187
Run1	0.312	0.321	0.1	0.267
Run2	0.277	0.285	0.2	0.238
Run3	0.24	0.25	0.3	0.21
Run4	0.208	0.214	0.4	0.178
Run5	0.17	0.18	0.5	0.15
Run6	0.138	0.142	0.6	0.12
Run7	0.104	0.106	0.7	0.09
Run8	0.069	0.071	0.8	0.06
Run9	0.03466	0.03561	0.9	0.02973

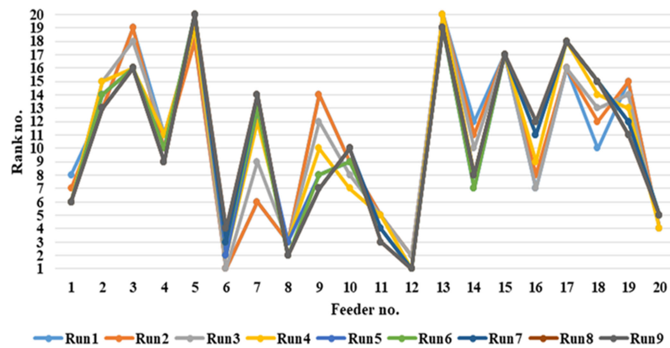

Fig. 3. Feeder prioritization for nine different weighting arrangements.

V. Conclusion

In order to effectively cut the cost of repairs and prevent potential widespread power outages, asset management practices in power systems should be performed with the proper allocation of maintenance budget and resources to critical feeders. This article proposed an MCDM framework to identify the critical feeders in power distribution systems. The process included two main steps: First, to determine the weights of criteria through which decision-makers can identify critical feeders, and second, prioritizing the feeders based on the weighted criteria and the severity of feeders' deterioration. SAIFI, SAIDI, ENS, and CIC metrics of reliability were defined as the decision-making criteria. Pairwise comparisons were performed by six experts and the decision criteria were weighted through BWM. Moreover, the FBWM was applied to overcome the prevailing uncertainty and vagueness in pairwise comparisons. Numerical results indicated that the CR obtained through the FBWM was lower than that when using the conventional BWM, which in turn, resulted in more reliable weights. The ENS and CIC were found the most and the least important criteria, respectively. Feeders were prioritized with respect to the given criteria through the TOPSIS technique in which F12 and F6 were identified as the most critical feeders. F13 was also the feeder with the best condition among all feeders and, therefore, was found less critical for maintenance. As a result, F12 and F6 should be inspected first to avoid the system shutdowns in the future. Sensitivity analysis was applied to examine the effectiveness of the final decisions. The results from the conducted sensitivity analysis verified that the optimal weights of the decision criteria have an indispensable role in finding the critical feeders.

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