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Identifying 6-Cluster Microgrid Resilience using Enhanced Partitioning Algorithm

Muhammad Zahid Bin Zainul Abidin[1], **Dalila Mat Said**[*1,2], **Nik Noordini Nik Abd Malik**[2], **Nasarudin Ahmad**[2] and **Mohammad Yusri Hassan**[1,2]

[1]Centre of Electrical Energy Systems, Institute of Future Energy, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor, Malaysia.
[2] Faculty of Electrical Engineering, Universiti Teknologi Malaysia, 81310 UTM Skudai, Johor, Malaysia.

[*]Corresponding author: dalila@utm.my

Abstract: In light of the growing effects of severe weather on power distribution network (PDN), enhancing resilience is critical. This research presents an advanced clustering method, referred to as the Enhanced Partitioning Algorithm (EPA), designed to establish the limits of microgrids (MGs) within a multi-microgrid (MMG) system. Unlike traditional methods, this approach partitions the PDN into 6 distinct microgrids to improve reliability. The power distribution systems are represented by nodes (buses) and edges (connections), and the analysis includes computation of the adjacency matrix, degree matrix, and Laplacian matrix. The EPA technique is a modification of conventional k-means clustering, utilizing grid-specific features such as terminal points for refined partitioning. Global silhouette coefficients (SC) are measured to evaluate the clustering performance. The method is applied to two IEEE benchmark distribution systems: IEEE 33 & 69 test bus systems. The results demonstrate clear, well-defined clusters with SC values exceeding 0.70, highlighting the importance of terminal points and connectivity patterns in supporting decision-making for grid partitioning. Analysis on the SC of the EPA is compared with the current method. The EPA approach offers researchers and practitioners an effective tool for enhancing the resilience and reliability of modern power grids.

Keywords: Clustering, hierarchical clusters, multi-microgrid, energy optimization, renewable energy sources

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1. INTRODUCTION

1.1 Motivation and Incitement

Extreme weather events have emerged as a critical factor contributing to power supply outages and the associated reliability and resilience challenges within PDNs. Recent years have seen an alarming increase in the frequency and severity of such events, resulting in widespread power outages and substantial economic losses. For instance, Hurricane Sandy in 2012 left approximately 8.1 million consumers without electricity in the Eastern United States, while the 2014 Typhoon Rammasun affected around 13 million customers in the Philippines. The Blyth Tornado in 2016 similarly disrupted the lives of about 1.7 million people in South Australia [1]. Notably, the February 2021 Texas winter storm illustrated the severe repercussions of such events, inflicting an estimated $195 billion in damages and impacting nearly 4.5 million homes [2].

MGs represent a promising solution to safeguard crucial loads (CLs) against such disruptions. Comprising distributed energy resources (DERs) like solar panels, wind turbines, and interconnected loads, MGs are characterized by their distinct electrical boundaries and locally regulated operations. By facilitating connections and disconnections from the main grid, MGs can function in both grid-connected and islanded modes. The potential for microgrids to operate synergistically beyond individual units gives rise to the concept of MMGs. These systems not only enhance reliability and power quality but also offer greater flexibility in managing renewable energy sources (RESs) [3]. However, the effective implementation of MMGs necessitates an innovative approach to their formation and management. This study introduces the EPA to identify the resilience of multi-microgrid systems through a structured clustering method, focusing on a 6-cluster approach tailored for modern power distribution networks.

1.2 Segmenting Active Distribution Network (ADN) into MMG Systems

Although these techniques offer valuable solutions, they do have certain limitations. For instance, references [4, 5] base the number of clusters on the quantity of generators, which might not be appropriate for all network setups. Likewise, reference [6] uses the k-medoids spectral clustering algorithm to select nodes for clustering, but the determination of the optimal number of clusters (k) is still somewhat subjective. This paper presents a new method to address this challenge by defining the boundaries of microgrids (MGs) during the design stage. Using the widely recognized k-means clustering algorithm, we propose a novel approach to select k based on the total number of end nodes, assessed using the Silhouette global coefficient.

End nodes in a power grid are particularly vulnerable to disruptions. These terminal points, which are connected by a single link, can experience significant effects from disturbances. Studying the clustering of end nodes enables the identification of areas in the network that need targeted attention for resilience planning. Moreover, this method is applicable to systems with varying bus configurations, independent of the number or location of RES and battery energy storage systems (BESS) within each MG. As a result, the boundaries of each MG remain clearly defined and resilient.

1.3 Clustering Techniques in Power Systems for Multiple Microgrids

Several clustering techniques are widely used in PDN to manage complexity, improve efficiency, and support decision-making in areas such as load forecasting, grid optimization, and distribution planning as documented in Table 1. Applications include load profiling [7], where clustering groups customers with similar consumption patterns to enable tailored demand-side management, and network partitioning, where it segments large grids into manageable zones, particularly in multi-microgrid systems for localized optimization. In [8], clustering optimum power balancing approach helps identify areas with similar distributed generation patterns for better grid integration. Common clustering techniques include K-means in [9], which partitions data into K clusters based on distance metrics for load classification with low economic cost and dimension control, while Sectionalizing switch location [10] leverages eigenvectors of similarity matrices for non-linear, highly connected networks. Hierarchical Clustering (HC) in [11], which builds a tree of cluster hierarchies, ideal for microgrid management on the energy flow and interactions between the Integrated Energy Cluster (IEC) and the main power grid. However, [12] used a three-layered hierarchical control framework to manage the energy across different time scales. Study in [13] shows Fuzzy C-Means (FCM) is useful for overlapping power flows, while Weight Graph Partitioning approach represents the power system as a graph. Reference [14] utilizes predetermined network topologies used to categorize residential, commercial, and industrial consumers. These clusters are designed based on load profiles and are key in managing Demand Response Programs (DRPs). Finally, reference [15] applied Density-Based Spatial Clustering of Applications with Noise (DBSCAN) to identify clusters based on the data density of frequency stability and rotor angle of the generator, proving effective in detecting outliers and faults in grid systems.

Table 1. A comparison of the proposed method with existing studies in the field of MMG construction

Ref	Focus	Methodology	Key Findings	Year
[5]	Best location for DG penetration in the distribution system	Weight Graph Partitioning Approach	Average Service Availability Index (ASAI) and Average Energy Not Supplied (AENS)	2023
[7]	Load shedding on sensitive loads and non-sensitive load at local and global optimization	Load Priority Based Nesting EMS	A hierarchical EMS is developed in which the algorithm makes price-based decisions	2021
[8]	Controllable distributed generation	Optimum Power Balancing	Consensus-Based algorithm for load shedding resilience index (LSRI)	2019
[9]	Cluster partition with economic cost, internal power balance and dimension control	K-means algorithm selection partitioning	Davies Bouldin Index (DBI) measure the quality of clustering effect through the correlation between clustering scenes	2022
[10]	Allocation of Energy Storage System (ESS) and ADN	Sectionalizing switch location	System average interruption frequency index (SAIFI), System average interruption duration index (SAIDI) and Customer average interruption index (CAIDI)	2020
[11]	Deman Response Market	Hierarchical Clustering	Deep Deterministic Policy Gradient (DDPG) with Multi-process (MP) and Priority Experience Replay (PER)	2024
[12]	Power transaction between distribution network operator and autonomous microgrid	Controllable Units Selection	AMG and DNO trading price curve	2022
[13]	False Data Injection Attack (FDIA) threat in smart distribution network	Fuzzy C Means (FCM)	Cluster Partition-Fuzzy Broad Learning System (CP-FBLS)	2024
[14]	Demand Response Program	Predetermined network topologies	Probability density function (PDF) measured to predict demand side management index (DSMI)	2020
[15]	Frequency stability and rotor angle of generator	DBSCAN spatial clustering	Correlation Coefficient (CC) criteria between all two pairs of synchronous generators	2022

2. FORMATION OF CLUSTERING IN MULTI MICROGRID

2.1 Clustering Methodology

Data Collection and Preprocessing: The process begins with the collection of data related to generation (solar, wind, etc.), load profiles, energy storage capacities, and geographical locations. This data is used to define features that will be used for clustering.

Feature Selection: Key features such as demand profiles, renewable generation potential, and geographical proximity are extracted. These features are essential in clustering microgrids because they reflect the operational and physical characteristics of the microgrids.

Clustering Algorithm: A k-means clustering algorithm is applied to partition the distribution network into optimal MMG configurations. The algorithm considers factors such as load similarity, geographical proximity, and network connectivity to form clusters that maximize efficiency and minimize losses.

Optimization Model Development: After clustering, an optimization model is developed to find the optimal sizing of generation and storage units within each microgrid cluster. The objective function typically minimizes costs (investment, operational, and maintenance) while ensuring energy balance and reliability.

Constraint Formulation: The optimization model includes constraints such as power balance, renewable energy penetration limits, grid interaction limits, and reliability metrics.

Cluster Validation: The resulting clusters are validated using silhouette analysis and Davies-Bouldin index to ensure that the partitions are both compact and well-separated. Adjustments are made to improve cluster quality if necessary.

2.2 Enhanced Partitioning Algorithm

Spectral graph analysis has been utilized to address challenges associated with the formation of microgrids and to evaluate the stability of power networks [19]. The electricity grid may be strategically segmented into smaller grids in response to an elevated risk of cascade failure. The segmentation of the grid into distinct, stable microgrids facilitates the execution of a sophisticated process referred to as islanding, which serves to alleviate the effects of cascading sequences on the electricity grid [16-18]. This study presents an improved partitioning algorithm derived from the conceptual framework of the spectral clustering method [19]. The proposed methodology is illustrated in Figure 1.

The initial phase involves the delineation of the system's line data, comprising branches that interconnect the buses. Each entry in the line_data array delineates a connection between two buses, thereby illustrating the system's connectivity. A total of 33 buses exists, with their interconnections elaborated upon through 32 branches. The adjacency matrix (W) of the system is constructed to represent the connections between buses, with entries of 1 signifying a connection between the respective buses.

$$W[i,j] = W[j,i] = \begin{cases} 1, & \text{if bus } i \text{ and } j \text{ is connected} \\ 0, & \text{otherwise} \end{cases} \tag{1}$$

After the adjacency matrix is established, the subsequent step involves calculating the degree matrix, a diagonal matrix in which each entry denotes the number of connections (or degrees) associated with each bus in the system. This matrix elucidates the interconnectivity of each bus within the system. A bar plot is created to visually depict the degrees of the buses, providing a rapid overview of the number of connections each bus has within the system, as illustrated in Figure 2.

$$D[i,j] = \sum W[i,:] \tag{2}$$

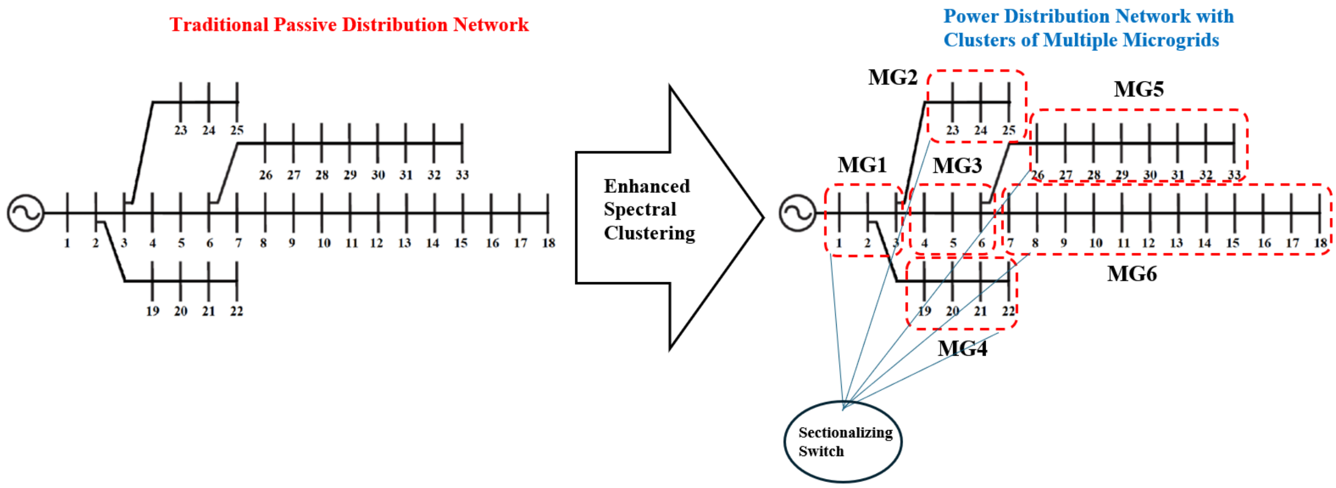

Figure 1. Proposed Active Distribution Network with clusters of MMGs

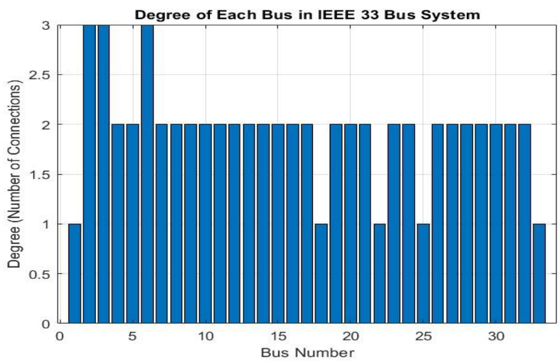

Figure 2. Degree matrix of IEEE 33 bus system

The difference between the degree matrix and the adjacency matrix is clarified in the definition of the Laplacian matrix (L) presented in Equation (3). The Laplacian matrix facilitates the comprehension of the graph's local structure.

$$L = D - W \tag{3}$$

The selected eigenvectors undergo normalization, followed by the application of K-Means clustering to categorize the buses into six distinct clusters. Each cluster signifies a potential microgrid, wherein buses exhibiting analogous operational characteristics are aggregated. The determination of the cluster number (k) was conducted by analyzing the characteristics of the terminal points; the aggregation of buses exhibiting a singular connection serves as the foundation for the clustering methodology. Figure 3 defines the comprehensive proposed MMG clustering process.

$$L \; x \; v = \lambda \; x \; v \tag{4}$$

These selected eigenvectors are normalized, and K-Means clustering is applied to group the buses into six clusters. Each cluster represents a potential microgrid, where buses with similar operational characteristics are grouped together. The cluster number (k) was determined by considering the properties of the terminal points; the total number of buses with only one connection forms the basis for the clustering process. Figure 3 illustrates the overall proposed MMG clustering process.

2.3 Clustering Validation

The evaluation of clustering quality is conducted through the calculation of global SC, which assess the degree of similarity of each bus to its respective cluster in relation to other clusters. The equation for the standard deviation of a single data point is articulated as follows [19]:

$$s(i) = \frac{b(i) - a(i)}{max\,\{a(i), b(i)\}} \tag{5}$$

where *s(i)* represents the SC for data point *i*, *a(i)* denotes the average distance from the *i-th* data point to other data points within the same cluster, reflecting cohesion. Conversely *b(i)* signifies the smallest average distance from the *i-th* data point to data points in a different cluster, indicating separation.

Equation (6) outlines the average silhouette score for cluster c, whereas equation (7) articulates the overall average silhouette score for the complete dataset.

$$AverageSC\ (c) = \frac{\sum \quad s(i)}{number\ of\ i\ in\ cluster\ c} \tag{6}$$

$$Overall\ AverageSC = \frac{\sum \quad s(i)}{total\ number\ of\ i} \tag{7}$$

The interpretations of the interval coefficient, as presented in Table 2, serve as a basis for evaluating the outcomes of SC interpretation.

Table 2. Average Interval Global Silhouette Coefficient

Type	Interval silhouette coefficient	Interpretation
1	0.71-1.0	Resilient framework
2	0.51-0.70	Acceptable framework
3	0.26 – 0.50	Inadequate framework
4	<0.25	No substantial structure identified

3. RESULTS AND DISCUSSIONS

This section assesses the effectiveness of the proposed methodology through its application to the IEEE 33-bus and IEEE 69-bus test systems. The clustering process is simulated using MATLAB. The subsequent sections detail the testing of a novel k-means spectral clustering technique, which employs an enhanced partitioning algorithm, applied to each of the specified systems, yielding a clustering solution. The findings are juxtaposed with alternative clustering methodologies, as illustrated in Table 7.

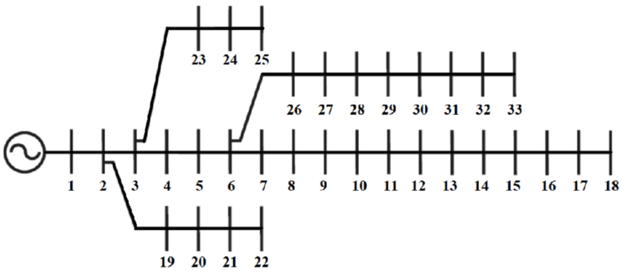

Figure 3. IEEE 33-bus test system

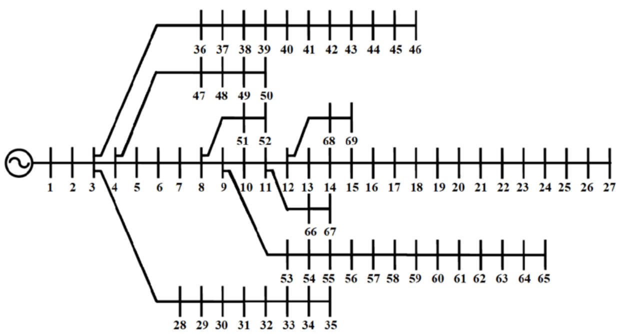

Figure 4. IEEE 69-bus test system

3.1 IEEE 33 bus test system with Spectral Clustering

The mean silhouette coefficient was computed to assess the efficacy of clustering, functioning as an objective measure of the overall quality of the clusters. Figure 5 illustrates a bar plot that delineates the silhouette score for each cluster, thereby offering a visual representation of the cohesion levels among buses across the 6 clusters.

Cluster 2 demonstrated the highest silhouette score of 0.8764, indicating a compact and internally cohesive structure. In contrast, Cluster 6 exhibited the lowest score of 0.6066, which implies diminished intra-cluster cohesion. The clustering technique produced a mean silhouette coefficient of 0.7052, suggesting a satisfactory clustering configuration.

The cluster with the highest score exhibits a closely integrated structure characterized by minimal distances among nodes, thereby underscoring its robust internal cohesion. Conversely, the cluster exhibiting the lowest score, especially in proximity to bus 2, demonstrates a more branched and potentially heterogeneous organization.

In order to facilitate the practical implementation of the proposed MMG partitioning strategy, Tables 3 and 4 present comprehensive compositions for each cluster. Table 3 delineates the buses categorized within each cluster, whereas Table 4 specifies the locations of the sectionalizing switches. Moreover, Figure 6 presents the modified IEEE 33-bus system, distinctly depicting each cluster alongside the total load associated with each, thereby enhancing the visual comprehension of the cluster configurations.

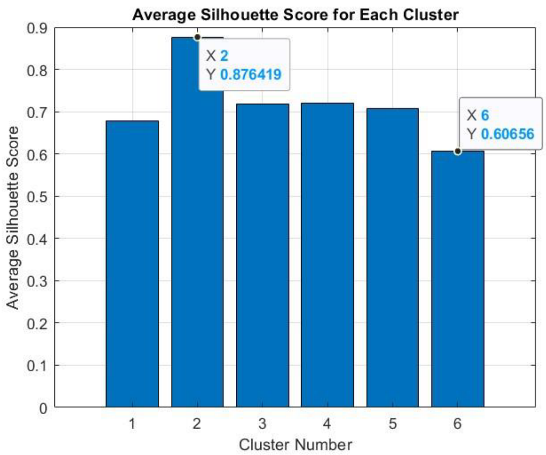

Figure 5. Mean Silhouette Score for each cluster in the IEEE 33 Bus System

Table 3. Results of network partitioning for each cluster within the IEEE 33 bus test system

Clusters	Bus Index
Microgrid 1	1, 2, 19, 20, 21, 22
Microgrid 2	3, 23, 24, 25
Microgrid 3	4, 5, 6, 7, 26, 27, 28
Microgrid 4	8, 9, 10, 11, 12, 13
Microgrid 5	29, 30, 31, 32, 33
Microgrid 6	14, 15, 16, 17, 18

Table 4. Location of the sectionalizing switch within the IEEE 33 bus test system

Clusters	Location
Microgrid 1	Line 2-3
Microgrid 2	Line 2-3, 3-4
Microgrid 3	Line 3-4, 7-8, 28-29
Microgrid 4	Line 7-8, 13-14
Microgrid 5	Line 28-29
Microgrid 6	Line 13-14

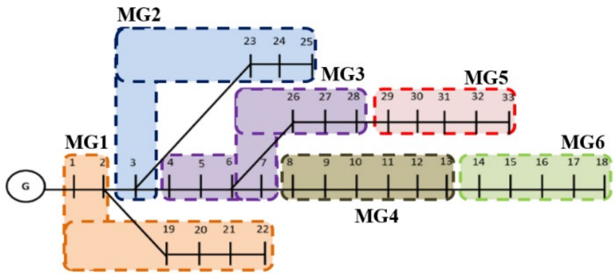

Figure 6. Proposed MMG formation of IEEE 33 bus test system

3.2 IEEE 69 bus test system with Spectral Clustering

In the IEEE 69-bus test system, Figure 7 presents a bar plot of the silhouette scores for each cluster, offering a visual assessment of the cohesion among buses within the six clusters. This plot provides a quantitative evaluation of clustering effectiveness, with the silhouette score indicating the strength of intra-cluster cohesion.

Cluster 1, exhibiting the highest score at 0.9168, demonstrates the most clearly defined and cohesive structure, while Cluster 3, with the lowest score of 0.5888, reflects comparatively weaker cohesion within its cluster.

The mean silhouette score, calculated at 0.7672, further substantiates the presence of a consistent and meaningful clustering structure. Tables 5 and 6 expand on the specific composition of each cluster: Table 5 lists the bus locations within each cluster, and Table 6 identifies the locations of sectionalizing switches. A closer examination of Table 5 and Figure 11 reveals that clusters with lower silhouette scores tend to encompass a higher number of buses, while clusters with higher scores generally contain fewer buses, highlighting an inverse relationship between cluster cohesion and bus count.

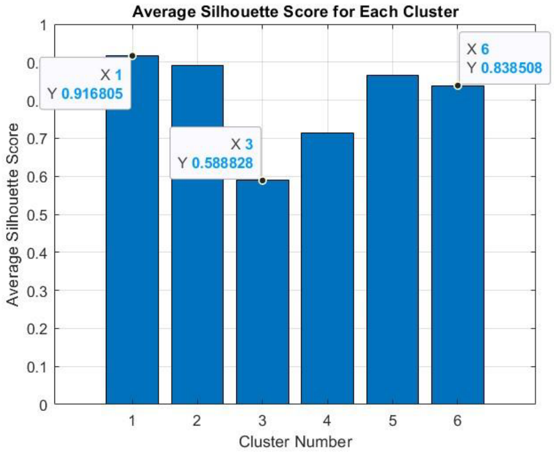

Figure 7. Mean Silhouette Score for each cluster in the IEEE 69 Bus System

Table 5. Results of network partitioning for each cluster within the IEEE 69 bus test system

Clusters	Bus Index
Microgrid 1	29, 30, 31, 32, 33, 34, 35
Microgrid 2	38, 39, 40, 41, 42, 43, 44, 45, 46
Microgrid 3	8, 9, 10, 11, 12, 13, 14, 15, 16, 17, 51, 52, 53, 54, 66, 67, 68, 69
Microgrid 4	1, 2, 3, 4, 5, 6, 7, 28, 36, 37, 47, 48, 49, 50
Microgrid 5	55, 56, 57, 58, 59, 60, 61, 62, 63, 64, 65
Microgrid 6	18, 19, 20, 21, 22, 23, 24, 25, 26, 27

Table 6. Location of the sectionalizing switch within the IEEE 69 bus test system

Clusters	Location
Microgrid 1	Line 28-29
Microgrid 2	Line 37-38
Microgrid 3	Line 7-8, 17-18, 55-54
Microgrid 4	Line 7-8, 28-29, 37-38,
Microgrid 5	Line 54-55
Microgrid 6	Line 17-18

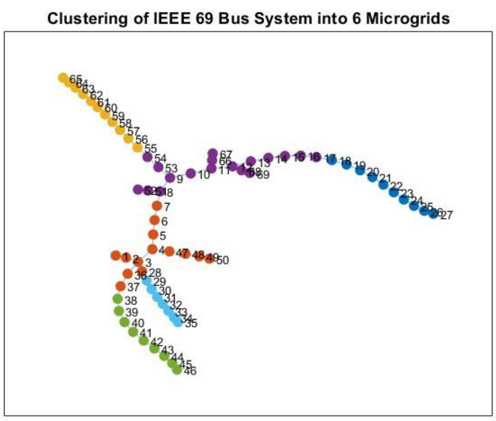

Figure 8. Proposed MMG formation of IEEE 69 bus test system

Table 7 summarizes the mean silhouette score of spectral clustering method and hierarchical clustering method using enhanced partitioning algorithm on IEEE-33 Bus System and IEEE 69 Bus System. The simulation is performed using MATLAB R2023b for each of the test systems.

Table 7. Mean Silhouette Score for IEEE 33 bus system and IEEE 69 system using two different methods

Power System	Method	Mean Silhouette Score
IEEE 33-bus system	Spectral Clustering	0.7052
IEEE 33-bus system	Hierarchical Clustering	0.3641
IEEE 69-bus system	Spectral Clustering	0.7672
IEEE 69-bus system	Hierarchical Clustering	0.3789

4. CONCLUSION

This research introduces a novel approach aimed at improving the resilience of Power Distribution Networks (PDNs) in light of the increasing challenges associated with extreme weather phenomena. This approach emphasizes the delineation of microgrids within a multi-microgrid system through the application of a k-means spectral clustering technique in conjunction with an improved partitioning algorithm. This methodology proficiently categorizes buses according to the characteristics of their terminal points. Furthermore, the formulation of the problem necessitates comprehensive modelling of power systems, encompassing nodes and connections depicted through adjacency matrices, degree matrices, and Laplacian matrices.

The evaluation of the clustering results is conducted through the application of Silhouette coefficients. The evaluations performed on the IEEE 33 and 69 bus systems demonstrate the presence of distinct clusters within each configuration, with an overall average Silhouette score consistently exceeding 0.70. The visualization of clustering outcomes underscores the method's efficacy, demonstrating strong physical interconnections among buses within each cluster and the lack of isolated buses that are devoid of physical links. The results highlight the importance of terminal points as essential elements in the decision-making framework for grid partitioning.

This study underscores the significance of terminal points in the clustering process, providing critical insights that can assist decision-makers and power engineers in optimizing grid partitioning, ultimately contributing to the resilience of PDNs. The findings of this study hold significant implications, especially in addressing the challenges posed by severe infrastructure disruptions in PDNs due to extreme weather events.

This study establishes a foundational framework for the formation of MMGs through the delineation of MG boundaries. Subsequent research endeavors will concentrate on the incorporation of DERs and islanding constraints to enable more feasible applications.

Explorations of this nature may encompass the optimization of Distributed Energy Resource (DER) sizing and the formulation of operational strategies for Microgrid Management Systems (MMGs) in both grid-connected and islanded contexts.

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