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Comparative Analysis of Different Clustering Techniques in Hybrid AC/DC Microgrid

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Abstract: *Rural electrification is a critical challenge in many developing countries, where conventional grid extension is often not feasible or cost-effective due to low load density and long distances. Hybrid AC/DC microgrids offer a promising alternative solution, providing a reliable and sustainable electricity supply to rural communities. This study presents a comparative analysis of four clustering techniques (hierarchical, k-means, fuzzy c-means, and gaussian mixture models) for optimizing cable routing by grouping loads in a low-voltage hybrid AC/DC microgrid in rural electrification areas. The proposed approach consists of several stages: (1) grouping loads into the clusters using four clustering techniques; (2) optimizing the radial topology in clusters of the microgrid by using minimum spanning tree (MST) and shortest path algorithms (SP); (3) balancing the three-phase system using mixed-integer linear programming (MILP); and (4) performing an economic analysis to evaluate the effectiveness of the four clustering techniques. The methodology is applied to a real case study of an island area in Cambodia, and the performance of a hybrid microgrid under different clustering configurations is compared. The results show that k-means clustering is the most cost-efficient solution for optimizing the topology of a hybrid AC/DC microgrid in rural Cambodia*.

Keywords: Clustering technique, Optimization, Hybrid AC/DC, Microgrid.

1. INTRODUCTION

Rural electrification is a vital factor for the social and economic development of any country, especially in developing countries like Cambodia, where more than 18% of the rural population still lacks access to electricity [1,2]. However, the extension of the centralized grid to remote and isolated areas is often impractical and costly due to the low demand, long distances, and difficult terrain [3]. Therefore, decentralized and renewable energy solutions, such as AC or DC grid, are considered a viable alternative to provide reliable and affordable electricity to rural communities.

In paper [4], the author explored the optimal radial topology of the LVAC distribution system using the shortest path algorithm (SPA) and the first-fit bin-packing algorithm (FFBPA). They suggested locations for photovoltaic (PV) installations within the network. However, the sizing of PV systems was determined through iterative techniques, and the placement of decentralized batteries was determined using a genetic algorithm (GA). In another study [5], a radial structure and phase balancing were sought through mixed integer quadratically constrained programming (MIQCP). Then, the GA algorithm was used to identify the maximum PV size to be injected into the system. Notably, these previous studies solely focused on the AC system. In this study, a low-voltage hybrid AC/DC microgrid planning approach is proposed, specifically based on DC loads. The DC structure is designed in a way that enables the AC main feeder to supply DC loads using AC/DC converters in each cluster. To achieve this, clustering techniques are employed. Clustering is a well-established unsupervised data mining technique used for data set segmentation [6] that is increasingly being applied in the electrical power system [7]. Previous research has utilized various unsupervised clustering algorithms, such as DBSCAN and GMMs, for classifying household electricity consumers [8]. Other studies [9], have employed fuzzy logic algorithms for optimal placement of distributed generation (DG) to minimize power losses and improve voltage profiles and power quality. In a specific paper [10], the author utilized K-means clustering to group DC loads, which facilitated the identification of the

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DC structure, optimal AC/DC converter locations, and electrical poles in an LV AC/DC microgrid in unelectrified regions. This approach offers potential cost reduction for AC/DC converters and conductors, ensures even distribution of DC loads across the cluster, and enhances the reliability and efficiency of the microgrid. Expanding upon previous studies, the researchers have not investigated the comparison of clustering techniques in the context of microgrid planning.

This study conducts a comparative analysis of four distinct clustering techniques for optimizing cable routing by grouping loads in a low-voltage hybrid AC/DC microgrid in rural electrification areas. The application and comparison of clustering techniques in this research serve the purpose of identifying the most suitable approach for load grouping and cable routing optimization, contributing to the design of efficient and cost-effective microgrid planning. The clustering techniques under consideration are k-means clustering, fuzzy c-means clustering, hierarchical clustering, and Gaussian mixture models clustering. The performance of these clustering techniques will be evaluated based on a comprehensive set of technical and economic criteria.

The rest of this paper is structured as follows: Section 2 provides a comprehensive explanation of the four clustering techniques and outlines the proposed methodology for designing the hybrid microgrid topology. Then, Section 3 presents the test case study and simulation results. Finally, Section 4 concludes the paper and offers valuable insights for future research directions.

2. METHODOLOGY

The process of designing the hybrid AC/DC distribution microgrid, illustrated in Fig 1, involves the following steps:

- **Step 1**: Input the system data, which includes the coordinates of MV/LV transformers, loads (households), power demand, electrical poles, and line impedances.
- **Step 2**: Apply four clustering algorithms (Hierarchical, K-means, FCM, and GMMs) to group the DC loads. The optimal number of clusters is determined using the Davies-Bouldin method.
- **Step 3**: Construct the minimum spanning tree to connect all DC loads inside each cluster.
- **Step 4**: Utilize the shortest path algorithm to determine the minimum length between each load and the poles. Then the AC/DC converters are placed on the pole based on the minimum DC power losses.
- **Step 5**: Perform a DC load flow analysis to ascertain the DC cross-section for each cluster. This should be based on the acceptable voltage and current requirements identified during DC load flow testing.
- **Step 6:** Allocate the DC clusters to different phases using a Mixed-Integer Linear Programming technique. This ensures the distribution is balanced.
- **Step 7**: Conduct an AC unbalance load flow analysis to determine the optimal AC cross-section of the main lines, taking into account technical constraints.
- **Step 8**: Analyze the cost consumption (CAPEX, OPEX, TOTEX) to evaluate the effectiveness of the four clustering techniques used in the system design.

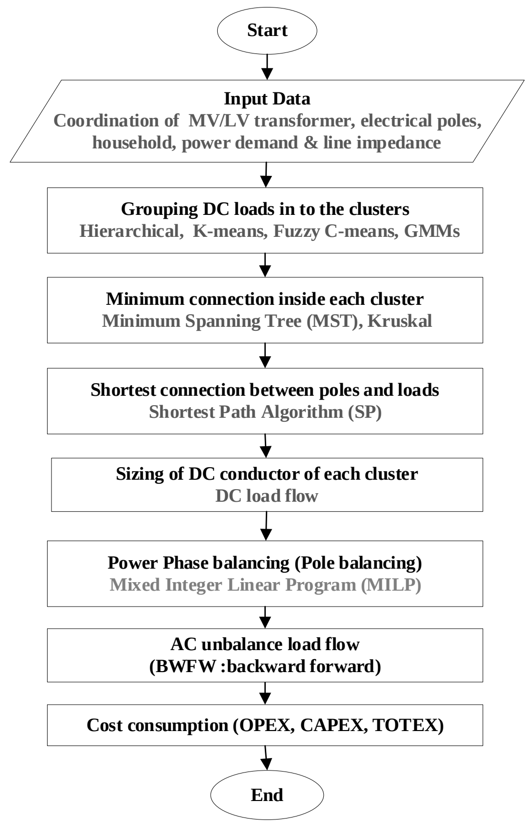


Fig 1. Flowchart of the process method

2.1 Clustering techniques

This section will provide an overview of the four clustering techniques employed in this study, namely agglomerative hierarchical clustering (AHC), k-means clustering, fuzzy c-means (FCM) clustering, and Gaussian mixture models (GMMs) clustering. Each technique is utilized to analyze and classify data in the context of hybrid AC/DC microgrid planning.

2.1.1 Agglomerative Hierarchical Clustering (AHC)

Agglomerative hierarchical clustering is a clustering technique that follows a bottom-up approach. It starts by considering each object as an individual cluster and then progressively merges clusters together until all objects are grouped into a single cluster [11]. here are three main categories of agglomerative hierarchical clustering based on the similarity measures or linkages used in the merging process. These categories are described in the following sections.

$$D_{\min}(X,Y) = \min_{x\in X, y\in Y} d(x,y) \quad \text{(Eq. 1)}$$

$$D_{\max}(X,Y) = \max_{x\in X, y\in Y} d(x,y) \quad \text{(Eq. 2)}$$

$$D_{average}(X,Y) = \frac{1}{|X||Y|}\sum_{x\in X}\sum_{y\in Y} d(x,y) \quad \text{(Eq. 3)}$$

Where, $D_{\min}$ is single linkage, $D_{\max}$ is complete linkage, $D_{average}$ is average linkage, x, y are data point, D is pair distance of data point x, y.

2.1.2 K-means Clustering

K-means clustering is a partitioning method that assigns data into k clusters. The main objective is to minimize the squared error of the distances to cluster centers, thereby reducing the total distance of the clusters [12]. The objective function J is defined as follows:

$$Minimize\ J = \sum_{j=1}^{K}\sum_{i=1}^{N}\left\|x_i^{(j)} - c_j\right\|^2 \quad \text{(Eq. 4)}$$

Where, i is the index of data point, j is the index of cluster, N is the number of data points, K is number of clusters, x is the data point, c is the cluster center.

2.1.3 Fuzzy C-means clustering (FCM)

Fuzzy c-means (FCM) is another method belonging to the K-centers family [13]. It shares similarities with K-means clustering, but in FCM, each instance is assigned a grade of membership to each cluster [14,15]. The objective function of FCM aims to minimize a certain criterion, as shown in Eq. (5). In fuzzy clustering, a load curve is not exclusively assigned to a single cluster. Instead, the degree of membership determines the extent to which a load curve belongs to each cluster, as shown in Eq. (6). An observation is assigned to the cluster with the highest membership degree [16]. The membership degrees are updated at each step according to Eq. (7).

$$J_m = \sum_{i=1}^{N}\sum_{j=1}^{K}\mu_{ij}^m\left\|x_i - c_j\right\|^2 \quad \text{(Eq. 5)}$$

$$\sum_{j=1}^{K}\mu_{ij} = 1 \quad \text{(Eq.6)}$$

$$\mu_{ij} = \frac{1}{\sum_{k=1}^{C}\left(\frac{\left\|x_i - c_j\right\|}{\left\|x_i - c_j\right\|}\right)^{\frac{2}{m-1}}} \quad \text{(Eq. 7)}$$

Where, J_m is the objective function to be minimized, N is the number of data points, K is the number of clusters, m is the fuzzy partition matrix exponent that controls the degree of overlap between clusters, μ_{ij} is the degree of membership of data point i-th to cluster j-th.

2.1.4 Gaussian Mixture Models Clustering (GMMs)

Gaussian Mixture Models (GMM) is a type of model-based clustering that uses a probabilistic model to cluster data, as denoted by Eq. (8). The model assumes that the data points are generated from a mixture of Gaussian distributions, where each Gaussian distribution represents a cluster. The algorithm proceeds iteratively to estimate the parameters of these Gaussian distributions, aiming to maximize the likelihood of the data given the model. The quality of fit of the model to the data is evaluated using the log-likelihood function, as expressed by Eq. (9). The parameters of the GMMs, including the mixing coefficient π_j, means μ_j, and covariance matrix Σ_j, are estimated using Eq. (10) through Eq. (12) [17,18].

$$p(x) = \sum_{j=1}^{K}\pi_j\mathcal{N}\left(x \mid \mu_j, \Sigma_j\right) \quad \text{(Eq. 8)}$$

$$\log p(x) = \sum_{i=1}^{N}\log\left(\sum_{j=1}^{K}\pi_j\mathcal{N}\left(x_i \mid \mu_j, \Sigma_j\right)\right) \quad \text{(Eq. 9)}$$

$$\pi_j = \frac{1}{N}\sum_{i=1}^{N}\gamma_{ij} \quad \text{(Eq. 10)}$$

$$\mu_j = \frac{\sum_{i=1}^{N}\gamma_{ij}x_i}{\sum_{i=1}^{N}\gamma_{ij}} \quad \text{(Eq. 11)}$$

$$\Sigma_j = \frac{\sum_{i=1}^{N}\gamma_{ij}(x_i-\mu_j)(x_i-\mu_j)^T}{\sum_{i=1}^{N}\gamma_{ij}} \quad \text{(Eq. 12)}$$

Where, x is the data point, N is the number of data point, j is the index of cluster, K is the number of clusters, γ is posterior probability, π_j is the mixing coefficient, $\mathcal{N}(x|\mu_j,\Sigma_j)$ is the multivariance normal distribution with means μ_j and Σ_j covariance matrix for cluster j.

2.1.5 Davies-Bouldin Index (DBI)

This study will utilize the Davies-Bouldin index to assess the optimal number of clusters for four clustering techniques. The index measures the average similarity between each cluster and its most similar cluster based on the ratio of within-cluster distance to between-cluster distance. A lower DBI value indicates better clustering quality [19].

$$DB_N = \frac{1}{K}\sum_{j=1}^{K}\max_{j\neq j'}\frac{\Delta(c_j)+\Delta(c_{j'})}{\delta(c_j, c_{j'})} \quad \text{(Eq. 13)}$$

Where, i and j are the index of cluster, K is the number of cluster, c is the cluster center, δ is the inter-cluster distance, Δ is the average distance.

2.2 Minimum Spanning Tree (MST), Krusal

A minimum spanning tree (MST) is a subset of the edges of a graph G that connects all vertices (nodes) together with the minimum total edge weight and without any loops (cycles). This algorithm was developed by J. B. Kruskal [20]. In graph G=(V,E), V represents the vertices and E represents the edges.

$$V = (v_1, v_2, ..., v_n) \quad \text{(Eq. 14)}$$

$$E = (e_1, e_2, ..., e_n) \quad \text{(Eq. 15)}$$

2.4 Costs Consumption

The total costs of the system are divided into capital expenditure (CAPEX) and operational expenditure (OPEX). The CAPEX includes the costs of cables, converters, and replacement costs, whereas the OPEX consists of the cost of energy purchased from the grid or transformer and maintenance costs [21]. The equations for CAPEX, OPEX, and TOTEX are written as follows:

$$CAPEX = C_{cable} + C_{converter} + C_{replacement} \quad \text{(Eq. 16)}$$

$$OPEX = \sum_{t=0}^{T} \frac{E_{grid} \times C_{elect/grid} + C_{maint}}{(1+r)^t} \quad \text{(Eq. 17)}$$

$$TOTEX = CAPEX + OPEX \quad \text{(Eq. 18)}$$

Where, $TOTEX$ is the total expenditure, $CAPEX$ is the capital expenditure, $OPEX$ operational expenditure, C_{cable} is cable cost [k$], $C_{converter}$ is converter cost [k$], $C_{replacement}$ is the replacement cost of converters, E_{grid} is energy purchased from grid [kWh], $C_{elec/grid}$ is the cost of purchased energy from grid [k$/kWh], C_{maint} is maintenance cost, r is discount rate [%], t is the index of time, T is planning year.

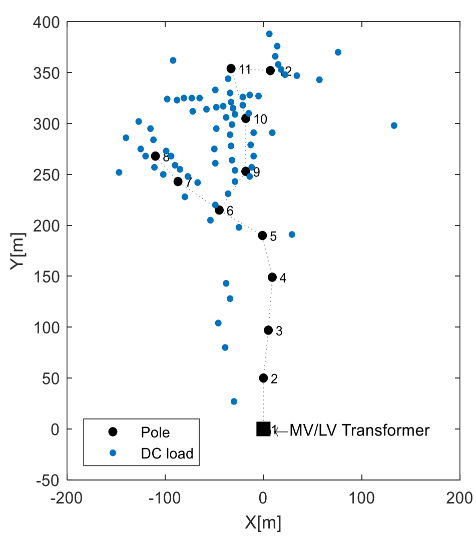


Fig 2. DC households and electrical poles.

3. RESULTS AND DISCUSSION

3.1 Input Data

Table 1 displays the input data employed in the simulation. The study centered on implementing diverse topologies through four clustering techniques, comparing them over a 25-year duration while excluding load growth from the analysis.

Table 1. Input data [22,23].

Items	Values
Planning period [years]	25
Discount rate [%]	6
AC/DC converter [k$/kW]	0.8
Converter lifetime [years]	15
Converter efficiency [%]	90
Converter maintenance cost [k$/kW]	0.0115
Cost of purchase energy from grid [k$/kWh]	0.000121
Cost AC cable 25 mm^2 [k$/km]	4.06
Cost DC cable 16 mm^2 [k$/km]	2.49
Cost DC cable 35 mm^2 [k$/km]	5.55
Cost DC cable 50 mm^2 [k$/km]	7.45

3.2 Case Study

Inn is a village situated in the southwestern region of Koh Rong Island, which is located in Preah Sihanouk province, Cambodia. This village is considered non-electrified and consists of 73 households with a total power consumption of 29.52 kW. Fig 2 illustrates the village's 12 electrical poles providing DC power, which are connected to an MV/LV transformer (22kV/0.4kV). The 50V DC voltage level was selected regarding the consumers in a rural area [24].

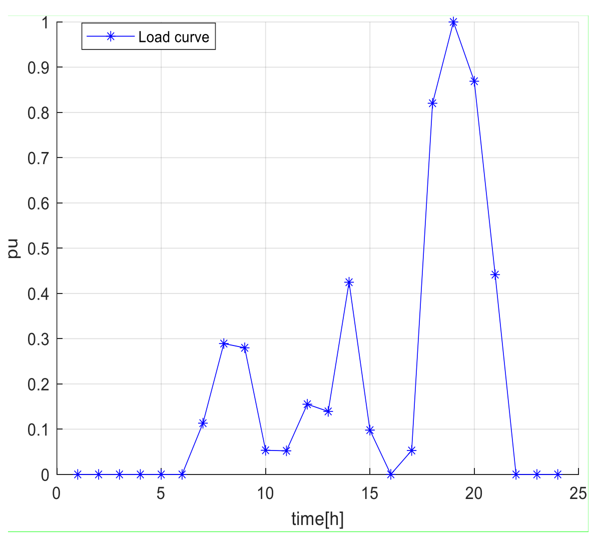
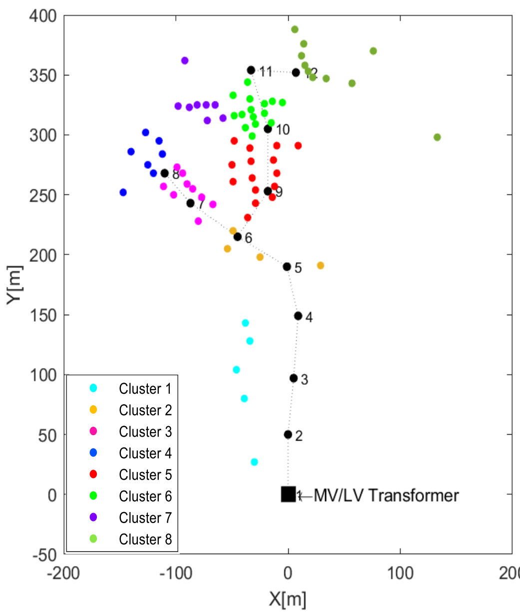


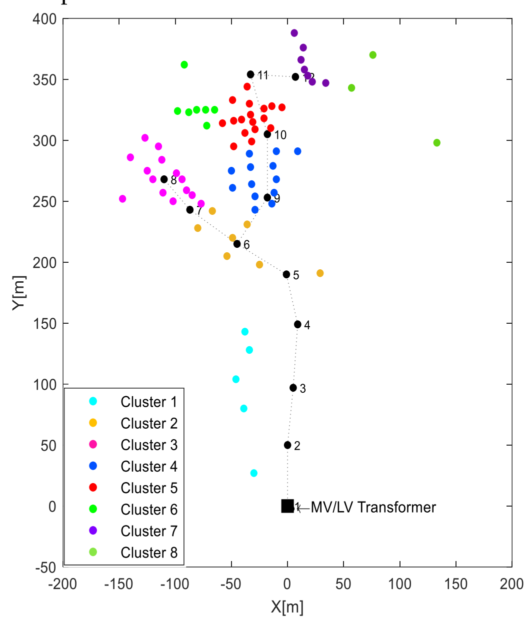
Fig 3. Daily loads curve.

Fig 3, the daily load curve of the case study is depicted, with the peak load occurring at 19:00. It is assumed that the yearly load curve repeats the daily load curve over 365 days due to the absence of electric heater usage by consumers.

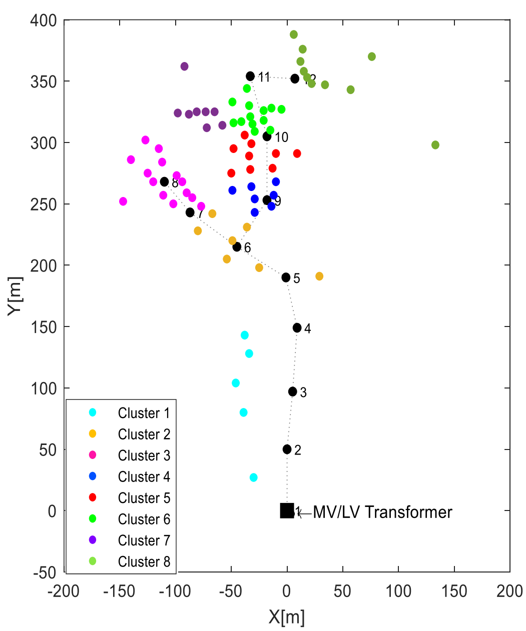
To achieve the objective, four different clustering techniques, namely AHC, k-means, FCM, and GMMs, were employed to categorize all the DC loads into eight clusters (k=8 clusters), as shown in Fig 4. The optimal number of clusters for each technique was determined using the Davies-Bouldin method (DB). By applying these techniques, it became possible to identify and visualize distinct clusters for the DC loads. In Fig 4, each cluster is visually represented by a unique color, which remains consistent for all the loads assigned to that specific cluster.



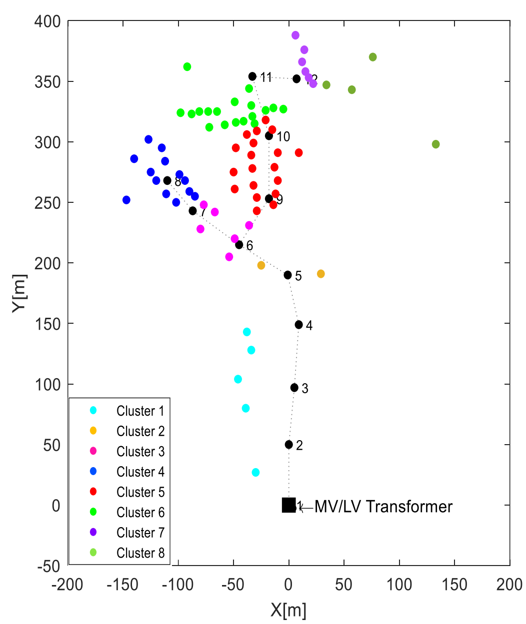
(a) Hierarchical clustering



(b) K-means clustering



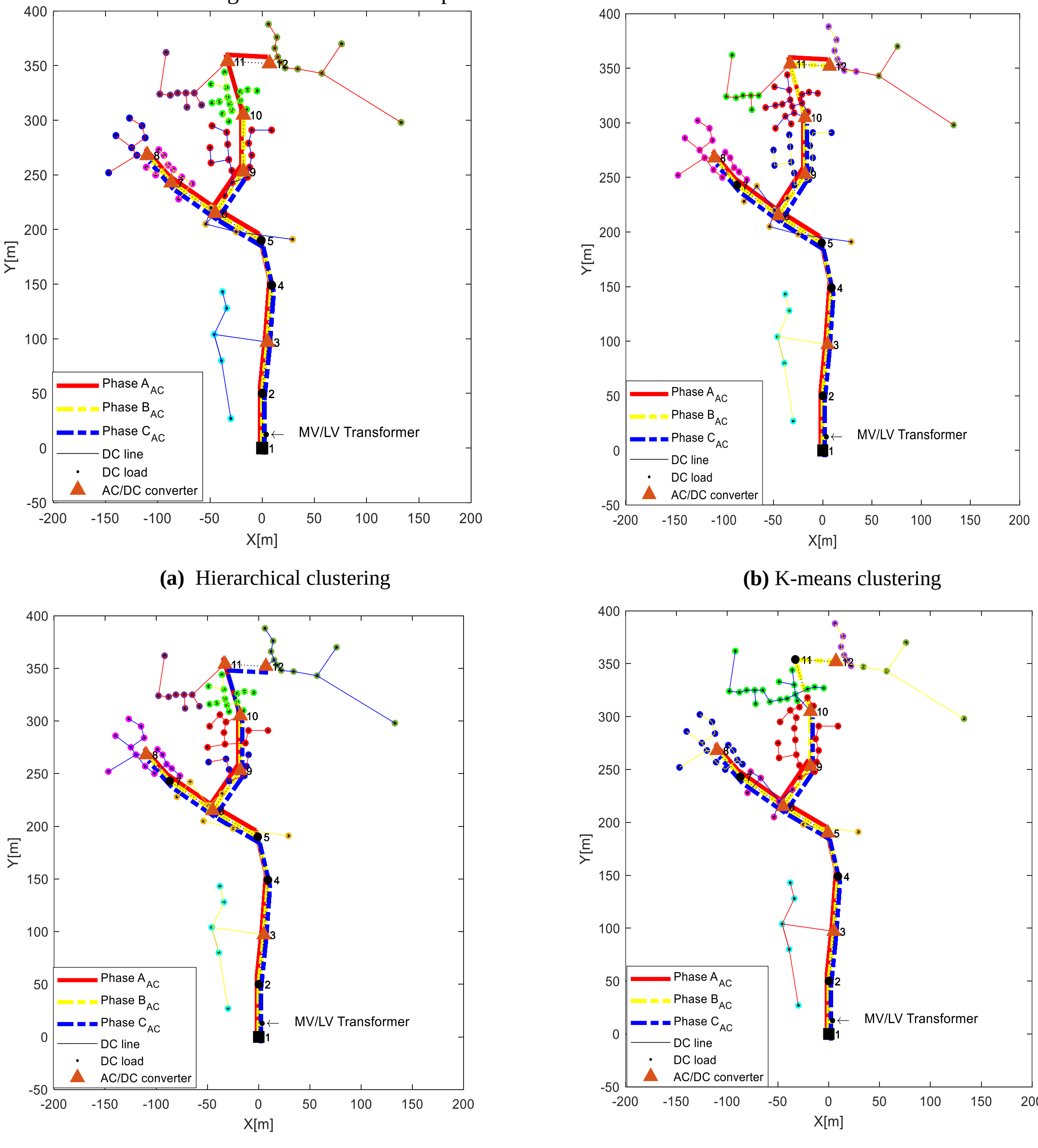
(c) FCM clustering



(d) GMMs clustering

Fig 4. Loads are classified by four clustering techniques.

To supply AC power to the DC loads in each cluster, a total of eight AC/DC converters are required. The Minimum Spanning Tree (MST) algorithm is utilized to calculate the minimum length of DC cable needed for each cluster. Furthermore, the Shortest Path (SP) algorithm is employed to determine the clusters connected to the poles where the AC/DC converters will be installed. Fig 5 illustrates the comprehensive hybrid AC/DC radial distribution system that incorporates four distinct clustering techniques. This system consists of multiple DC clusters that receive power from 3-phase, 4-wire sources via AC/DC converters. To meet voltage constraints specified by the low voltage system regulation [0.90 pu, 1.1 pu], the cross-section of DC cable was selected shown in Table 2 and the AC main feeder was chosen as 25 mm2.



(a) Hierarchical clustering

(b) K-means clustering

(c) FCM clustering

(d) GMMs clustering

Fig 5. Complet hybrid AC/DC distribution system from difference clustering.

In Fig 5, the color of the DC lines representing each cluster has been adjusted to reflect the phase connection of the respective cluster. This visual representation helps to identify the phase allocation and highlights the distribution of clusters across the three-phase system. By utilizing the MILP algorithm and considering phase allocation, the AC/DC distribution network achieves a balanced and efficient topology, supporting reliable power delivery to the clusters while maintaining load equilibrium in the AC distribution system. Table 3 presents a comparison result of four different clustering techniques applied to the design of a low-voltage hybrid AC/DC microgrid topology for a 25-year planning period.

Table 2. DC crosssection of four clustering techniques measured over a period of 25 year.

DC cross-section (mm^2)								
Clusters No.	1	2	3	4	5	6	7	8
Hierarchical	16	16	70	35	25	70	35	35
K-means	16	35	50	50	70	25	16	25
FCM	16	35	25	50	35	50	35	35
GMMs	16	10	25	50	70	70	16	25

Table 3. Results of comparison of hierarchical k-means fuzzy c-means and GMMS and clustering for a 25-year planning period.

Items	Hierarchical	K-means	Fuzzy C-means	GMMS
Number of clusters	8	8	8	8
Number of converters	8	8	8	8
Total length of DC conductor (m)	2380	2368	2434	2442
Total length of AC conductor (m)	1832	1830	1925	1940
Total energy loss (MWh/year)	3.308	3.223	3.320	3.326
Energy purchased from grid (MWh)	1515.375	1510.225	1515.5	1516.075
CAPEX (k$)	57.855	56.709	58.501	59.948
OPEX (k$)	109.198	108.844	109.213	109.247
TOTEX (k$)	167.053	**165.553**	167.715	169.195

Based on Table 3, four techniques (AHC, K-means, FCM, and GMMs) resulted in the same number of clusters and converters, indicating that the load grouping was consistent between the four methods. This suggests that both techniques were successful in dividing the load into distinct clusters, facilitating effective cable routing.

When evaluating the physical layout of the microgrid, the total length of the AC and DC conductor was found to be lower in the K-means clustering, measuring (2368 m) and (1830 m), respectively compared to the other three clusterings. This indicates that K-means was successful in minimizing the distances between the DC loads and converters, as well as between the AC loads and the grid connection point.

In terms of energy performance, the K-means clustering exhibited slightly lower energy losses with a value of 3.223 MWh/year compared to the other techniques. This suggests that the K-means clustering technique may have been more effective in minimizing energy losses within the microgrid. Regarding the energy supply from the grid, four techniques showed similar results, with the HAC clustering requiring the purchase of 60.615 MWh/year, the K-means clustering requiring 60.409 MWh/year, the FCM clustering 60.620 MWh/year, and GMMs requiring 60.643 MWh/year. This indicates that both designs had comparable dependencies on the external grid for energy supplementation.

Considering the economic aspects, K-means clustering showcased superior cost-effectiveness by considering both capital expenditure (CAPEX) and operational expenditure (OPEX), resulting in a lower total expenditure (TOTEX) of 165.553 k$ among the four techniques. This suggests that K-means achieved a favorable trade-off between investment and operational costs, surpassing the performance of the other three techniques

Overall, the analysis results obtained from each clustering technique revealed slight differences in the physical layout, energy performance, and economic implications of the microgrid design. However, the K-means clustering outperformed to the other three clustering in terms of minimizing, cable routing, energy losses, and achieving cost optimization. Therefore, the K-means clustering technique is recommended for the concept of hybrid AC/DC microgrid planning in rural areas of Cambodia, as it offers improved energy efficiency and cost-effectiveness.

Fig 6 displays a spider diagram that outlines the relevant features of four clustering techniques, namely hierarchical, k-means, FCM, and GMMs, for designing a hybrid microgrid.

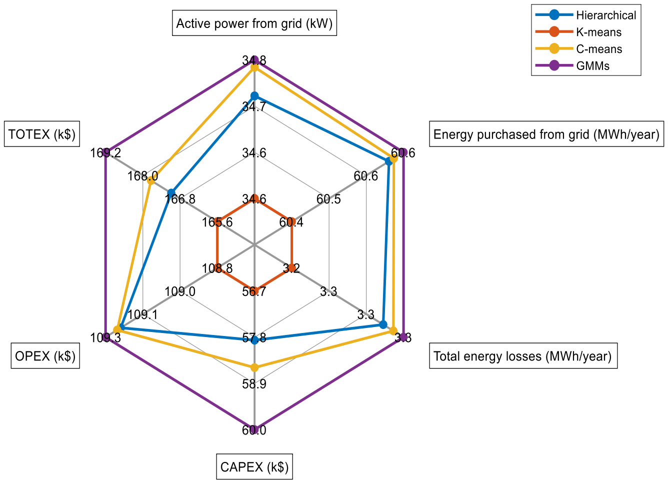


Fig 6. Comparison of hierarchical, K-means, FCM and GMMs clustering techniques.

4. CONCLUSIONS

This study aimed to compare four clustering techniques (hierarchical, k-means, fuzzy c-means, and GMMs) for designing a low-voltage hybrid AC/DC microgrid in rural electrification areas of Cambodia over 25 years. The comparison was based on an array of technical and economic criteria. The entire methodology was implemented in a real-world scenario involving an island area in Cambodia. The results indicated that the k-means clustering exhibited lower energy loss and energy purchased from the grid, with values of 3.223 MWh/year and 60.409 MWh/year, respectively, compared to the other three clustering techniques. This suggests that the k-means technique efficiently balanced the energy supply and demand within the system, resulting in reduced reliance on the grid. However, k-means clustering emerged as the most cost-effective option, considering both capital expenditures (CAPEX) and operational expenditures (OPEX). This resulted in the lowest total expenditure (TOTEX), amounting to 165.553 k$. The findings indicate that k-means successfully struck a better balance between investment and operational costs compared to the other techniques. The study underscores the effectiveness of clustering techniques in developing cost-efficient microgrids in rural areas.

As a future direction to enhance this research, we recommend exploring the optimal locations and dimensions for photovoltaic (PV) systems and energy storage units within the microgrid cluster, considering load growth, seasonal load variation, and uncertainty. This would facilitate greater integration of renewable energy sources, enhancing the overall sustainability and resilience of the system and making it more resistant to fluctuations in load demand.

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