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Virtual Microgrid Partitioning Considering Structure and Characteristics of Smart Distribution Networks

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Abstract- One key element that limits the transition of conventional distribution networks (DNs) to smart distribution networks (SDNs) is its infrastructure and used technologies which are not originally designed to be integrated with distributed energy resources. To address this limitation, Virtual Microgrids (VMs) concept is used for upgrading DNs to SDNs. The core issue for developing VMs is to identify its boundaries. Therefore, this paper presents a strategy that aims to identify VMs boundaries for conventional DNs to be upgraded to SDNs, considering both structure and characteristics of power networks. The proposed method is tested on IEEE 33-bus system, in which both modularity and line losses were used to evaluate its effectiveness. Furthermore, feasibility of the proposed algorithm is validated on a larger IEEE 118-bus system. Subsequently, IEEE 33-bus and IEEE 69-bus systems are used to test the impact of PV penetration increment on the VM design. The numerical results show that the proposed partitioning strategy can identify lines which has the highest resistivity and least transmitted power.

Keywords Virtual microgrid, community detection, partitioning, clustering, distributed generation, photovoltaic.

1. Introduction

Nowadays, with the increase of environmental awareness of climate change, unstable fuel costs and outdated electricity grid infrastructure and technologies, there have been initiatives from governments and institutes to move towards smart grid and green energy. Renewable Energy Sources play a key role in the smart grid design however research on integrating them to the existing infrastructure show many challenges [1-4]. The complexity of the system is increased by the interconnection of the Distributed Energy Resources (DERs). Further complication occurs when the consumers also generate some energy on their own, using home based solar panels [5][6]. Distribution networks are designed to be unidirectional networks. They deliver electrical power to customers in the most economical way possible for centralized systems and that required them to be fixed and not feasible to be integrated with distributed generation resources (DERs). Since it is not reasonable or economically possible to redesign DNs for entire cities, detailed research on how to upgrade the existing distribution networks to fit the use of DERs in the most economical and convenient way should be done. One of the most popular concepts for upgrading conventional distribution networks that have drawn much attention lately is virtual micro-grids (VMs). VMs concept has the ability to upgrade conventional distribution networks. It is based on partitioning the DNs into a group of areas or microgrids. While there is no general agreement among researchers on the definition of VMs, VM concept will be discussed in detail and summarized according to previous literature in the following section.

The study of power network partitioning using various approaches has been broadly studied. Authors in [7] proposes an optimum power system network partitioning method for detecting community structures in power networks and dividing them into communities while reducing intercommunity V-Q sensitivity and Q power imbalance. A partitioning method that uses a combination of the optimization problem's Hessian matrix and the admittance matrix as the affinity matrix to determine the partition by grouping strongly computationally coupled buses and weakly coupled buses to different areas using the spectral clustering technique.is proposed in [8]. An island partitioning approach based on energy risk evaluation utilising supply–demand balance was presented by the author in [9]. Authors in [10] presented a portioning approach based on electrical distance and voltage control capabilities to address voltage violation problems caused by significant penetration of PV units. They presented a two-layer voltage control approach that incorporates both cluster and distributed inter-cluster optimization. By updating the intra-cluster optimal solution and the virtual slack bus voltage, cluster autonomous optimization may avoid intra-cluster voltage violation. In [13], a multifaceted partitioning method for power networks using K-means algorithm tool is presented where electrical distance was taken as an important factor. Based on these reviews, all previous partitioning methods are effective for specific purposes rather than considering the topology of the power distribution networks.

Complex network theory has gotten a lot of attention in studying power network systems. In [14], the authors presented a methodology for evaluating the performance of alternative multivoltage-level distribution network design strategies, as well as a statistical algorithm based on fractal theory to realistically model consumer settlement and network topologies for multivoltage-level distribution networks. In [15], authors developed a method which is based on defining a new similarity index, and it can be used to locate communities and investigate the impact of bridging nodes on power grid cascading failure. By improving the Newman community detection algorithm to be implemented as a power grid partitioning algorithm, a functional community structure based on weighted network model was developed by authors in [11] and [12]. The electrical coupling strength (ECS) was used as a measure to detect communities. Therefore, techniques for detecting communities in complex networks offer a lot of potential for VM identification in distribution networks.

The main contributions of this paper include the following: 1. Study features and characteristics of VMs and propose a definition which sum up characteristics and working principles of VMs. 2. Propose a methodology for partitioning distribution networks using both its structure and power flow ability to identify the lines with highest resistivity and least power transmission significance.

The remainder of this work is structured as follows. Features and characteristics of VMs as well as virtual microgrid boundaries are summarized and explained in Section 2. The methodology on the proposed community detection in power networks are explained in Section 3. Meanwhile, Section 4 and Section 5, present the case studies and numerical results of the proposed partitioning method when it is applied to the IEEE 33-bus, IEEE 69-bus and IEE 118-bus systems. Finally, Section 6 concludes the paper by highlighting the major conclusions and contributions of the work.

2. Virtual Microgrid

Until now, there is no agreement on a particular definition of VMs. K. Anoh in [13] defined VM as “an aggregation of small-scale prosumers in order to operate as a single controlled entity which has the ability to manage the aggregated units; and control the electrical energy flow between these units in order to obtain better operation of the system.” Authors in [14] define VMs as “entities where energy prosumers are orchestrated into bigger associations with the goal of optimizing the association’s benefits. Meanwhile, authors in [15] defines VMs specifically as an “integration of all kinds of distributed power sources, distributed energy storage system, energy-saving source in a certain region by multilayers of cloud platform control center; implementing virtual Internet, ubiquitous communication and flexible configuration, while keeping microgrid characteristics internally balanced.” A recent study by I. Xiaotong Xu in [12] proposed a definition of VMs considering previous research as follows: “Virtual microgrids are virtually islanded systems based on the structure of conventional distribution networks (CDNs), they have the similar control strategies and operating modes as microgrids and can adapt to the future requirements of SDNs.”

Based on previous research and understanding of the VM concept, in this research the following definition is proposed and shown in Fig. 1: “Virtual microgrids are virtually islanded systems developed from conventional distribution networks (CDNs) where each partition must contain enough distributed energy resources to maintain the following electrical characteristics: self-adequacy, self-sufficiency and self-healing; and have information and communication technologies (ICTs) between partitions for optimized energy management.”

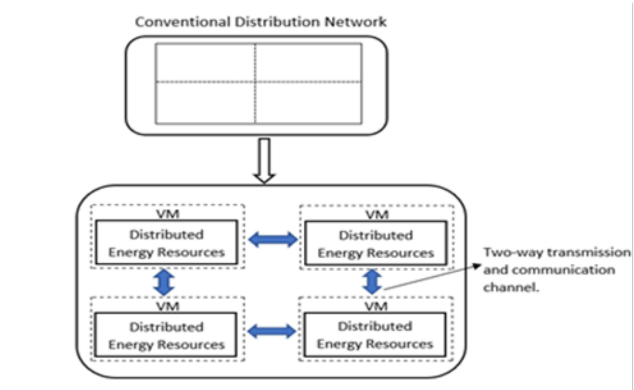

Fig. 1. Illustration of the basic concept of VM [12].

Self-adequacy refers to the ability to keep power generation and consumption balanced within each VM [14][15]. Self-healing is the capability of autonomous restoration after faults or disturbances [15]. Self-sufficiency in DNs refers to minimizing power flow between different VMs, and the imbalance between generation and loads within each VM [16-18].

Most of the suggested methods which are aimed to identify VMs boundaries are based on analyzing the operating states of power network [13]-[16]. An interesting approach done by [12] introduced a partitioning strategy based on structural characteristics of power networks. In this work, a virtual microgrid framework is introduced considering both structure and operating states of power networks; where a clear-cut investigation of power network structure along with the power transmitted between buses is done.

To achieve the electrical characteristic of VMs which is self-sufficiency, VM design should have some features from a structural point of view. This refers to dense electrical connection inside VMs while relatively sparse electrical connection between different VMs. This feature can also meet one of the goals of optimal power distribution operations, which refers to transmitting power with the least losses.

3. Methodology

This section describes a methodology that is proposed in this work for VM design. The aim is to optimally partition the distribution network integrated with distributed PV generation by minimizing line losses. This is a crucial first step in order to pick the optimal location and capacity for energy storage, which is the research's final step. The presented technique that uses distribution system data, a PV generation model, and a load model as inputs. The procedure's decision variables are distribution line resistivity and transmitted power.

3.1. Structure of Power networks

While complex network theory is a popular topic in computer, brain and social networks' applications, research considering the structure of power networks along with their operating states are lacking. Power grid is a system of high-voltage transmission lines that allows electric power to be transported over great distances both inside and between countries. Different networks are represented by simplified graphs in complex network theories, which consist of two basic elements: nodes (vertices) and edges (links). To be able to represent and analyze the power grids in a simplified manner, some graph concepts that are related to power networks are used and shown in Figures. 2-5.

The nodes and edges referred to in this work correspond to elements of power distribution network. Fig. 2 shows three kinds of edges in complex networks. Edges refer to links between two nodes (for instance, edge between node 1 and node 2). Multi-edges represent the presence of more than one edge connecting two nodes (for instance, edges between node 2 and node 3). A self-edge is a link connecting one vertex to another. (For instance, the edge in node 4.) Because electrical networks are usually used to transmit power from one node to another, this project's work is based on nodes with one edges and multi-edges.

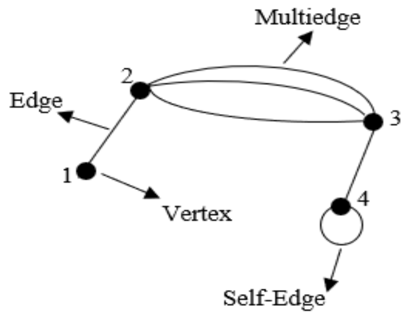

Fig. 2. A diagram of different components in complex networks.

A directed network, also called a digraph, is a network where every edge has a direction, pointing from one node to another. These edges are called directed edges, or sometimes arcs, and are be represented graphically by, for instance, lines with arrows on them as in Fig.3.

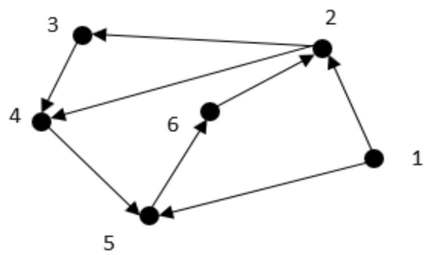

Fig. 3. A directed network.

Even though power networks may seem like directed graphs since they transmit power from one node to another, in this research, power networks are considered undirected graphs. This enables the analysis of the whole network considering the existence of DERs and energy trading.

The two forms of complex networks that are typically examined are unweighted and weighted networks, with the latter being significantly more difficult to evaluate. The links between any two nodes in an unweighted network are either present or absent. For example, social networks are an unweighted network in which two types of potential links exist between people: either they know each other, or they do not. A N×N adjacent matrix A can be used to describe the connection in an unweighted network. Imagine i and j are two nodes in a network, the element $A_{i,j}$ in matrix A can be written as

$$A_{i,j} = \begin{cases} 1, & \textit{there is an edge between node i and j} \\ 0, & \textit{otherwise} \end{cases} \quad (1)$$

So, in a social network, if there is a connection between i and j and they know each other then $A_{i,j} = 1$ but if they do not then $A_{i,j} = 0$.

Edges in unweighted networks indicate basic binary connections between nodes; they either exist or they do not. However, in some cases, representing edges as having a strength, weight, or value, generally a real integer, is beneficial. As a result, edges in a social network may have weights that indicate the strength of people's relationships. Predator–prey interactions in a food web may have weights that measure total energy transfer between prey and predator. Weights may be assigned to network lines to reflect the quantity of data passing through them or their bandwidth. Such weighted can be represented mathematically by an adjacency matrix with the elements $A_{i,j}$ equal to the weights of the corresponding connections. So, the adjacency matrix is written as:

$$A_{ij} = \begin{pmatrix} 0 & 3 & 1 \\ 3 & 0 & 2 \\ 1 & 2 & 0 \end{pmatrix} \tag{2}$$

Where A_{ij} represents a weighted network in which the connection between node 1 and 2 is 3 times stronger than node 1 connection with node 3. Also, it is noticed that node 2 and 3 have a connection weight of 2. Nodes 1,2 and 3 have no weight among themselves which indicate that there are no self-edges for the 3 nodes. This weighted graph can be illustrated in Fig. 4.

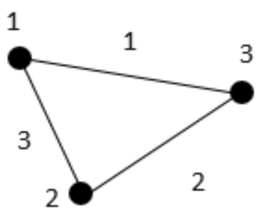

Fig. 4. A weighted network.

In Fig. 5, the nodes with the same colour belong to the same community, and it can be seen that the nodes in the same community have more physical connections than the other nodes in the network. To be able to utilize network communities concept to obtain the goal which is transmitting power with the least losses (minimizing the distance between nodes and minimize power flow between communities of VMs), it is needed to compare it to VMs characteristics. Because VMs are self-sufficient systems, their electrical connections should be higher than those of other nodes in the network, resembling the features of communities in complex networks. As a result, community detection algorithms in complex networks has high potential for solving power network partitioning problems [8].

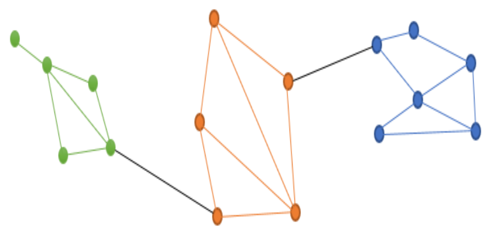

Fig. 5. A network with 3 communities.

The problem of finding groups of nodes in networks is called community detection. Community detection is a challenging task as the problem is not very well posed. Broadly speaking, the aim of community detection is to locate natural partitions of a network into groups of nodes with multiple edges inside and few edges between them. This description, however, is vague and open to interpretation—what exactly do we mean by "multiple" edges or "few"? To turn community detection into a problem that can be tackled quantitatively, numbers or indexes are required to be included on these concepts. The most widely used approach is the method of modularity maximization. A number of methods on community detection have been developed and shown good results in practical situations [24-30].

The task of community detection is approached as an optimization problem. The method of community detection is the optimization of modularity. Modularity is a scale value between -1 and 1 that measures the density of edges inside communities to edges outside communities. Theoretically, the best possible grouping of nodes in a given network may be obtained by optimising this value. Heuristic algorithms are used since it is difficult to go through all possible iterations of the nodes into groups.

3.2. Community Detection in Power Networks

This study proposes an approach of community detection in power networks based on both the structural characteristics and power flow of the networks. This is achieved by formulating the network structure and transmitted power in the optimization problem equally. Specifically, the optimization will minimize the distance between buses and power flow between boundaries of VMs as illustrated in Fig.6. Since CDNs structure is already formed and is unlikely to be changed, the structural parameters of the distribution lines (line electrical distance and line capacity) are fixed. So, calculation of the electrical distance is based resistance; the reactance is ignored in calculating electrical distance since resistance is much higher than the reactance in distribution lines. Also, the capacity of the distribution lines is considered as a limit of how much can be transmitted within VMs' distribution lines rather than a parameter of the VM design itself. So, to minimize electrical distance, the reciprocal of resistance, which is conductance, is used and is defined as follows:

$$\overline{G_{ij}} = 1/R_{ij}, \quad i,j \in A \tag{3}$$

where R_{ij} is the electrical distance between bus i and bus j. A refers to all the buses in the network.

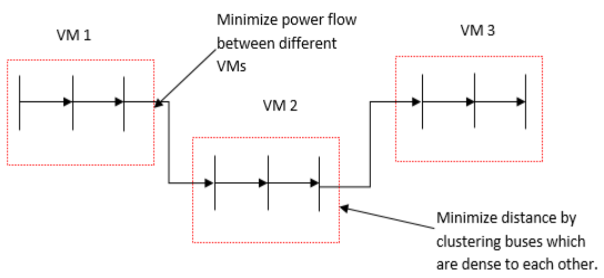

Fig. 6. Illustration of concept of minimizing distance among buses in and minimizing power flow between different VMs.

To incorporate transmitted power within the distribution lines in the planning stage of the VM, the transmitted power in each line is calculated based on load of its receiving bus. Since VMs are supposed to be self-sufficient, the power flowing between lines within the VM should be proportional to the load of the receiving bus. This concept is illustrated in Fig. 7.

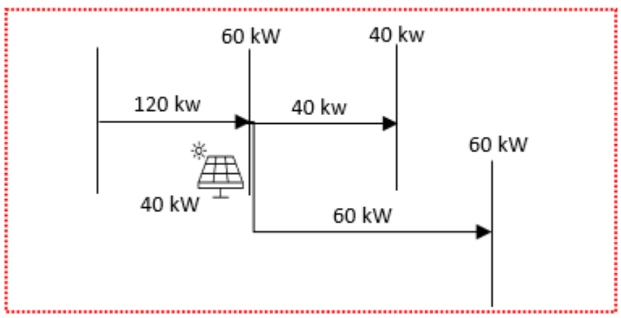

Fig. 7. Illustration of power transmission within distribution lines

The line transmitted power is defined as follows:

$$\overline{P_{ij}} = L_j \quad i,j \in A \tag{4}$$

where L_j is the real load power at bus j. The peak load of the receiving bus represents the actual value of transmitted power in the transmission line over a period of a time. To represent a 24-hour scenario of load and PV profile, energy is used instead of power in the composite weight. Energy for 24 hours is defined as:

$$\overline{E_{ij(24)}} = \sum_{n=1}^{24} L_{nj} - PV_{nj} \quad i,j \in A \tag{5}$$

Where L_{nj} is the real load power in bus j at hour n and PV_{nj} is the PV generated power in bus j at hour n. The input data used for VM clustering are normalized using feature scaling as follows:

$$x' = \frac{x - x_{min}}{x_{\max} - x_{\min}} \tag{6}$$

where x is an original value, x' is the normalized value. x_{min} and $x_{\max}$ are the minimum and maximum values of the data. In order to obtain partitioning results that incorporate both the transmitted power of lines and electrical distance, the composite weight index is defined as:

$$\overline{W_{ij}} = \left|\alpha \overline{P'_{ij}} + j\beta \overline{G'_{ij}}\right|, \quad i,j \in A \tag{7}$$

where P' is the normalized active power, G' is the normalized conductance, α and β are proportion coefficients; and α = β =0.5.

The value to be optimized is modularity, which has a value between −1 and 1. For a weighted graph, modularity is defined as:

$$Q = \frac{1}{2m}\sum_{ij}\left[\overline{W_{ij}} - \frac{k_i k_j}{2m}\right]\delta(c_i, c_j) \tag{8}$$

Where: $W_{\{i,j\}}$ represents the edge weight between nodes i and j. $k_{\{i\}}$ and $k_{\{j\}}$ are the sum of the weights of the edges attached to nodes, respectively. m is the sum of all of the edge weights in the graph. $c_{\{i\}}$ and $c_{\{j\}}$ are the communities of the nodes and δ is Kronecker delta function ($\delta_{\{x,y\}} = 1 \; if \; x = y, 0 \; otherwise$).

The Louvain algorithm proposed in [30] is a heuristic algorithm for maximizing modularity over divisions of a network into any number of communities. The Louvain algorithm is an agglomerative algorithm, which works by taking single nodes and joining them into groups, then joining groups with other groups, and so forth, in an effort to find the configuration with highest modularity. The partitioning process was developed by replacing the modularity Q by the electrical modularity and the community detection process is shown in Fig. 8.

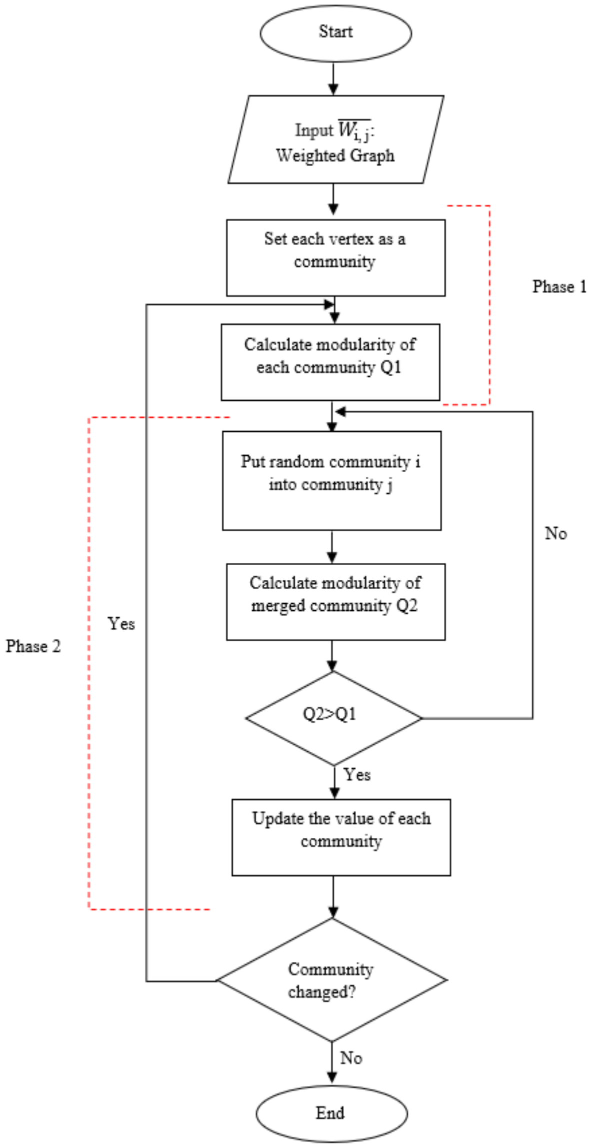

Fig. 8. Community detection process using Louvain Algorithm.

3.3. Losses Calculation

Energy losses for each VM were calculated as the total line losses within the VM using (9)

$$VM_L = \sum_{n=1}^{24} PL_n, \quad PL \in VM \tag{9}$$

Where PL_n is the line power losses at hour n for lines within the VM.

4. Case Study

Using the structure and characteristics of power networks presented in sections 2 & 3, the power network is perceived as a weighted undirected graph. The proposed methodology was tested on IEEE 33-Bus, IEEE 69-Bus and IEEE 118-Bus systems as shown in Fig. 9-11. The PV profile of a sunny day were recorded for every 30 minutes from Solar Lab PVSG in the main campus of UTeM, Durian Tunggal, Melaka, Malaysia and is shown in Fig 12. Also, hourly load profile that represents typical Malaysian residential distribution network demand [31] is shown in Fig. 13. The demand profile shown in Fig.13 shows that the demand is higher during the night when people come back from work and early in the morning when they wake up to get ready to go out than demand at other time.

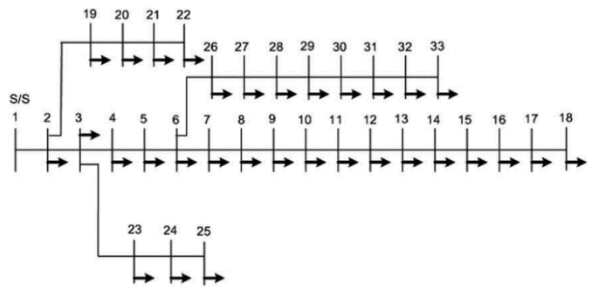

Fig. 9. IEEE 33-bus radial distribution system.

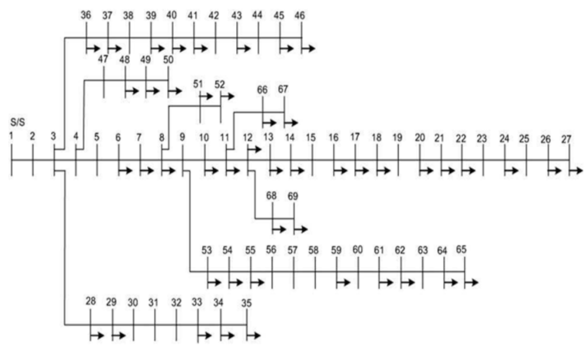

Fig. 10. IEEE 69-bus distribution system.

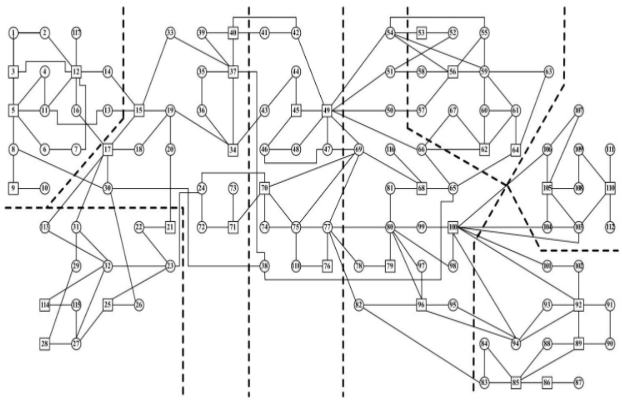

Fig. 11. IEEE 118-bus system.

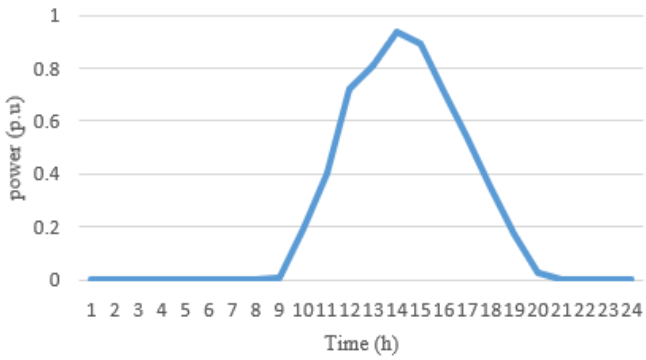

Fig. 12. PV Profile.

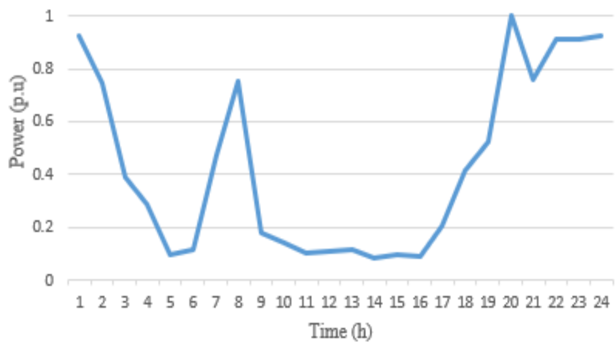

Fig. 13. Load Profile.

The developed method was applied on IEEE 33-Bus network and compared the results of VM design in terms of cut-sets, modularity, and line losses for the first three cases. Also, in order to validate the feasibility of the proposed algorithm on a larger system, we tested it on the IEEE 118-bus system as shown in Table 1. Table 2 and Table 4 list some of the values of computed weight of lines for the IEEE 33-Bus and IEEE 118-Bus networks, respectively.

Table 1. Description of the study cases.

Cases	Type of input	Input weight	Test system
1 [12]	Structure of distribution lines	Susceptance and line capacity W(S)	IEEE 33-Bus distribution system
2	Structure of distribution lines	Conductance W(G)	IEEE 33-Bus distribution system
3	Structure and transmitted power of distribution lines	Conductance and power flow W(P, G)	IEEE 33-Bus distribution system
4 [11]	Electrical coupling strength	Transmission capacity and equivalent admittance W(C, Y)	IEEE 118-Bus system
5	Structure and transmitted power of distribution lines	Conductance and power flow W(P, G)	IEEE 118-Bus system

Table 2. Computed weight of some lines for IEEE 33-Bus test system.

From bus	To bus	Case 1 W(S) [12]	Case 2 W(G)	Case 3 W(P, G)
1	2	18.2797	10.84599	0.714671
8	9	1.2796	0.970874	0.035382
9	10	1.2796	0.957854	0.034846
12	13	0.9053	0.681199	0.028307
13	14	1.3209	1.846381	0.163506
14	15	1.7309	1.692047	0.076746
2	19	5.5918	6.097561	0.386741
19	20	0.8146	0.664805	0.084853
20	21	1.8893	2.442002	0.149783
21	22	1.0558	1.410636	0.099414

Table 3. Computed weight of some lines for IEEE 118-Bus test system.

From bus	To bus	Case 4 W(C, Y) [11]	Case 5 W(P, G)
3	5	1.263	0.00997578
5	6	-	0.134270696
8	9	0.779	0.098531273
11	13	-	0.087462899
12	14	-	0.037446802
16	17	2.156	0.028575021
17	18	2.412	0.154406073

To incorporate PV generation profile in the VM design, 24-hours energy formulated in (5) is used instead of power as the composite weight index. The proposed partitioning method that considered the 24 hours energy is tested on the IEEE 33-bus and IEEE 69-bus distribution networks with solar PV generation. Then, the impacts of solar PV increment and distribution on the VM design are evaluated. As it is assumed that VMs are self-adequate and self-sufficient systems; PV stand-alone system will not satisfy those characteristics without energy storage. Since placement and control of energy storage will take place in the following process of the study, PV generation for designing VM will be perceived as if they satisfy the load during night regardless of missing the energy storage.

5. Results

This section presents the findings of this work, in which IEEE 33-Bus network was partitioned and the results of VM design were compared in terms of modularity and line losses for study Cases 1-3 shown in Table 1. IEEE 118-bus system was used and compared to a previous study in cases 4 and 5 to validate the feasibility of the proposed algorithm to a larger system. The impact of solar PV generation to the VM design was tested on the IEEE 33-bus and IEEE 69-bus distribution systems where different penetration levels and locations were assigned for PV systems.

5.1. Verification of VM Design

5.1.1. IEEE 33-Bus Distribution System

Fig. 14 and Table 4 present the results of VM designs for the first three cases as stated in Table 2. These results consist of the modularity, cut sets and line power losses. Result in Table 4 shows that the proposed partitioning method has resulted in the highest modularity (Q = 0.77) which indicate a very dense partition compared to the approach presented in [12] (Case 1) and Case 2. Consequently, that the third case which considers both structure and transmitted power in the weightage formulation has given the least line power losses; followed by Case 2 which uses conductance; and finally, Case 1 [12] with the highest line power losses. Since the main purpose of this method is to minimize line losses, it is expected that the lines with the highest resistance are used as boundaries and lines with similar lines resistance are grouped into one partition. VMs' boundaries depict in Table 5 and Fig. 14 prove this expectation as communities with a resistance close in range are grouped together and any sudden increase in resistance in one of lines was identified as a cut-set. For example, line 19-20 has a resistance of 1.5042 Ω comparing to the range of resistance of VM 1 which are between (0.0922 Ω and 0.164 Ω). Also, VM 5 which has cut-set lines (8-9) of high resistivity (1.03 Ω) compared to the resistance range within the VM (0.1872 Ω and 0.7114 Ω). A significant difference in the partition of the three cases is VM3. The partitioning of VM3 into two VMs (VM3 and VM8) in case 3 reduced the total power losses. VM3 line losses in both case 1 and case 2 is (0.705760 MW) while the total line losses for VM3 and VM8 in case 3 is (0.691027 MW). These results verify that the proposed partitioning method is suitable and effective in identifying the optimal VM design for minimizing the power losses in distribution network.

5.1.2. IEEE 118-Bus System

To validate the feasibility of the proposed algorithm to a larger system, we tested it on the IEEE 118-bus system. The optimal partitioning results for the 118-bus are a division into 12 VMs with electrical modularity equal to 0.77. The result was compared to the partition in [11] with an electrical modularity of 0.072. Table 5 shows the electrical modularity, partitioning results and line power losses for both cases.

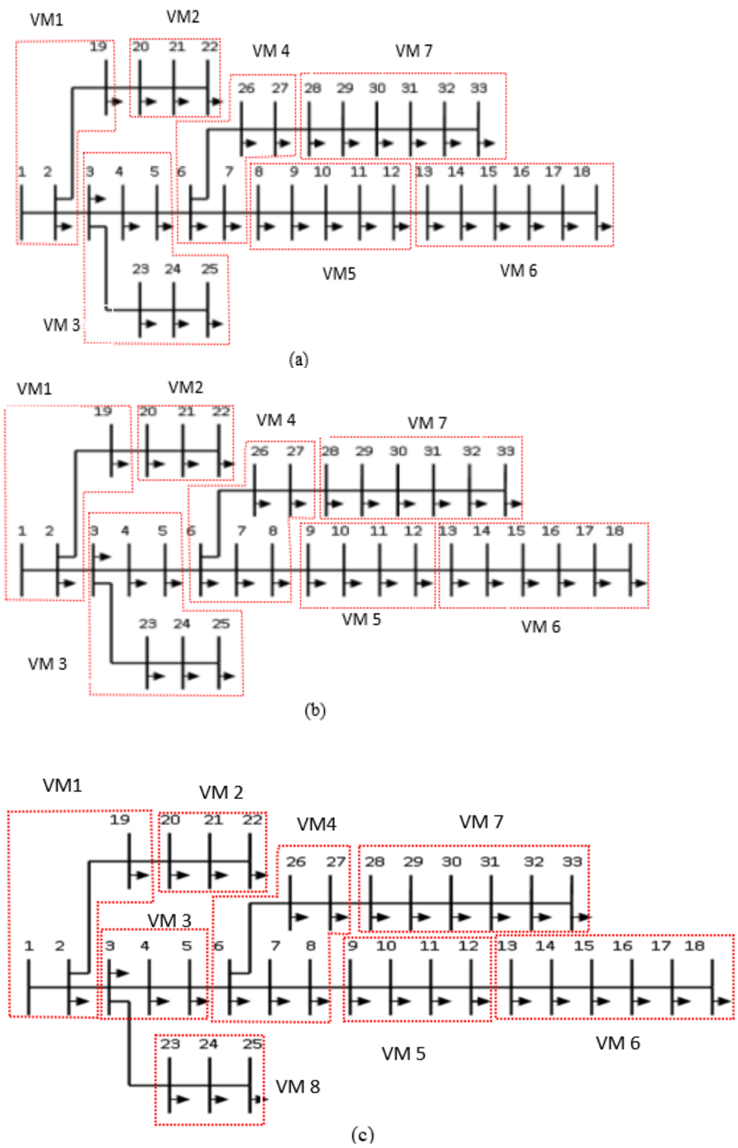

Fig. 14. Partitioning results for IEEE 33-bus distribution network. (a) Case 1 [12] (b) Case 2 (c) Case 3.

Table 4. VM designs for different case studies for IEEE 33-bus distribution network.

Case	Modularity Q	Power Losses in VM (MW)	Total Power Losses (MW)
1[12]	0.71	**VM1**:0.143049 **VM2**: 0.001628 **VM3**: 0.70576 **VM4**: 0.126523 **VM5**: 0.235301 **VM6**: 0.037551 **VM7**: 0.224537	1.474348
2	0.75	**VM1**: 0.143049 **VM2**: 0.001628 **VM3**: 0.70576 **VM4**: 0.228297 **VM5**: 0.11839 **VM6**: 0.037551 **VM7**: 0.224537	1.459212
3	0.77	**VM1**: 0.143049 **VM2**: 0.001628 **VM3**: 0.662642 **VM4**: 0.228297 **VM5**: 0.11839 **VM6**: 0.037551 **VM7**: 0.224537 **VM8**: 0.028385	1.444478

Table 5. VM designs for different case studies for IEEE 118-bus system network.

Case	Q	Bus number in each VM	Power Losses in VM (MW)	Total Power Losses (MW)
4[11]	0 .072	**VM1**: 1-7, 11-24, 27-29, 31-33, 70-76, 113-115, 117, 118 **VM2**: 8-10, 25, 26, 30, 34-69, 116 **VM3**: 77-112	**VM1**:24.329 **VM2**:55.548 **VM3**:38.287	118.17
5	0.77	**VM1**: 1.-7, 11, 12, 16, 117 **VM2**: 8-10, 26, 30, 38 **VM3**: 13-15, 17-22, 33-36, 43, 113 **VM4**: 23, 25, 27-29, 31, 32, 114, 115 **VM5**: 24, 69-82,118 **VM6**: 37, 39, 40-42, 44-50, 57 **VM7**: 51-56, 58, 59, 63, 64 **VM8**: 60-62, 66, 67 **VM9**: 65, 68, 116 **VM10**: 83-88 **VM11**: 89-97, 102 **VM12**: 99-101, 103-112	**VM1**:3.0953 **VM2**:13.958 **VM3**:4.4699 **VM4**:14.071 **VM5**:17.176 **VM6**:16.309 **VM7**:3.1889 **VM8**:1.0863 **VM9**:0.1299 **VM10**:2.612 **VM11**:12.15 **VM12**:12.55	100.81

5.2. *Impact of solar PV generation to the VM design*

To investigate the impact of PV penetration on the VM design, the proposed partitioning method that considered the 24 hours energy was tested on the IEEE 33-bus and IEEE 69-bus distribution networks with solar PV generation. The two distribution systems were tested by varying PV penetration levels and by changing PV allocation in the distribution network.

5.2.1. Variation of PV Penetration Level

PV was installed on every bus in the test systems for different penetration levels (20%,40%,60%,80% and 100%) of the total load. Result obtained from these tests were the same as the one obtained using the W (P, G) weight index except for 100% of the load which provided the same results using the weight index of the conductance alone W(G). Since power was injected to all buses in a balanced manner the weight index did not change and therefore provided the same VM boundaries.

5.2.2. Variation of PV Distribution

5.2.2.1. IEEE 33-bus system

To test the validity of this method to reflect on power change in the VM design, the PV was injected in an unbalanced manner for two different cases as follows: 1. Case A: PV Penetration level of 60% for busses at the end of the network bus 9-13, 15-18. 2. Case B: PV Penetration level of 100% for buses with load under 200 kW. VM designs of the test systems under both considered scenarios are shown in Fig.15 and Table 6. Table 6 points out the cut sets change from the initial W (E, G) design. Transmitted power for 24 hours (energy) and line resistance for the cut sets and lines connected to them are also shown to point out the significance of the chosen line to be the cut set. As seen in Cases A and B, lines with the least transmitted power over time (energy) was chosen to be the cut sets. In cases where the line has the same amount of transmitted energy as the one connected to it, line with the highest resistivity was chosen as the cut set. Line 6-7 and line 7-8 in Case a are an example of that scenario. However, line 12-13 in Case a was used as a cut set even though it transmits more power than line 11-12. The reason for that is the significantly higher resistance of line 12-13 which 1.468 Ω to the resistance of its connected lines 11-12 and 13-14 which are 0.3744 Ω and 0.5416 Ω, respectively.

5.2.2.2. IEEE 69-bus system

The weight index used to represent the 24-hour load alone is calculated and partitioning results for IEEE 69-bus test distribution system is shown in Fig.16. PV is then added to the system in unbalanced manner for two different cases as follows: 1. Case A: one PV is installed on busses with loads at the middle of the network bus Bus7-9. 2. Case B: 100% of the load for buses with load under 100 kW is supplied. The cut sets change from initial W (E, G) design is shown in Table 7 where it is shown that lines with lowest energy transmission and highest resistivity were chosen as the cut sets.

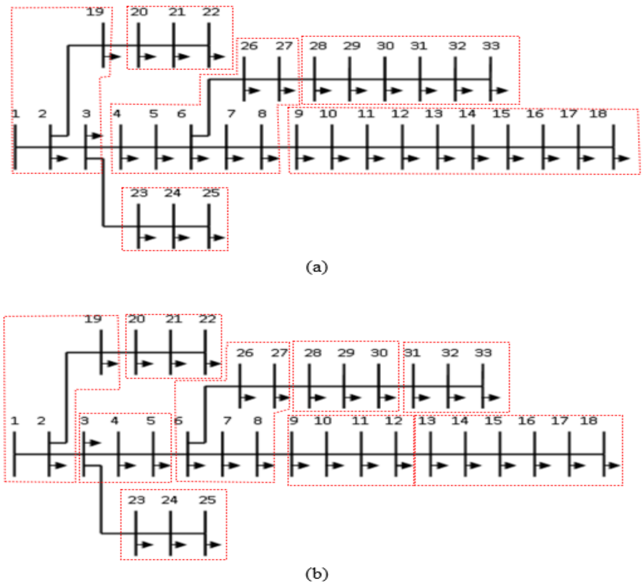

Fig. 15. Partitioning results for IEEE 33-bus distribution network considering load and PV profiles. (a) Case 1 (Q= 0.72) (b) Case 2 (Q = 0.79).

Table 6. Partitioning results for IEEE 33-Bus distribution network including load and PV profiles.

Case	Cut sets change from initial W (E, G)	Energy transmitted in the chosen cut set line compared to VM lines (MWh)	Line resistance in the chosen cut set line compared to VM lines (Ω)
A	L29-30 L7-8 L12-13	L28-29: 1.2401 **L29-30: 0** L30-31: 1.5501 L6-7: 0 **L7-8: 0** L8-9: 0.62 L11-12: 0.4650 **L12-13: 0.6200** L13-14: 0.6200	L28-29: 0.8042 **L29-30: 0.5075** L30-31: 0.9744 L6-7: 0.1872 **L7-8: 0.7114** L8-9: 1.03 L11-12: 0.3744 **L12-13: 1.468** L13-14: 0.5416
B	L30-31	L29-30: 1.8668 **L30-31: 0** L31-32: 1.9701	L29-30: 0.5075 **L30-31: 0.9744** L31-32 0.3105

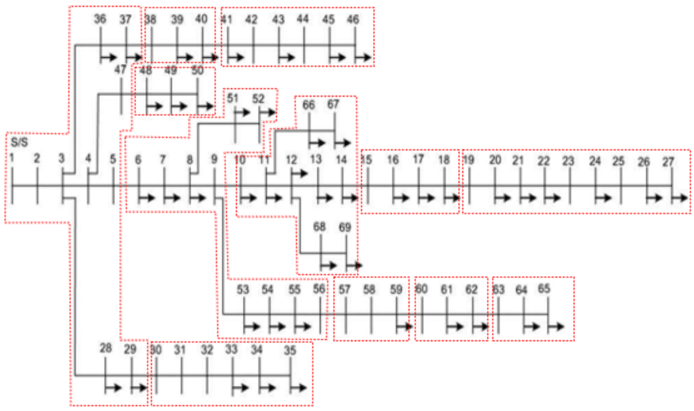

Fig. 16. Partitioning results for IEEE 69-bus test distribution system based on the method formulated in (5) W (E, G) (Q=0.77).

Table 7. Partitioning results for IEEE 69-bus distribution network including load and PV profiles.

Case	Cut sets change from initial W (E, G)	Energy transmitted in the chosen cut set line compared to VM lines (MWh)	Line resistance in the chosen cut set line compared to VM lines (Ω)
A	L11-66 L12-68	L10-11: 1.4984 **L11-66: 0** L66-67: 0 L11-12: 1.4984 **L12-68: 0** L68-69: 0	L10-11: 0.1872 **L11-66: 0.2012** L66-47: 0.0047 L11-12: 0. 7114 **L12-68: 0.7394** L68-69: 0.0047
B	L9-53	L8-9: 0.1949 **L9-53:0.0450** L53-54: 0.2728	L8-9: 0.0493 **L9-53: 0.1740** L53-54:0.2030

6. Conclusion

This paper discusses the features and characteristics of VMs and proposes a definition for VMs according to previous literature. A method for identifying VMs boundaries for residential distribution networks, considering both structure and characteristics of power networks using virtual microgrid concept is done. Through analyzing the results of IEEE 33 and IEEE 118 networks, it can be concluded that the method used in the paper can describe the structural characteristics of distribution networks very well, and the partitioning method can determine the boundaries for VMs while providing the least losses. After that, the analysis was done to investigate PV increment effect on the VM design for residential network on IEEE 33-bus and IEEE 69-bus distribution networks and showed that lines with highest resistivity and least power transmission significance were used for the VM cut sets.

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