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Importance Assessment of Multiple Microgrids Network Based on Modified PageRank Algorithm

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Abstract

This paper presents a comprehensive scheme for assessing the importance of multiple microgrids (MGs) network that includes distributed energy resources (DERs), renewable energy systems (RESs), and energy storage system (ESS) facilities. Due to the uncertainty of severe weather, large-scale cascading failures are inevitable in energy networks. making the assessment of the structural vulnerability of the energy network an attractive research theme. This attention has led to the identification of the importance of measuring energy nodes. In multiple MG networks, the energy nodes are regarded as one MG. This paper presents a modified PageRank algorithm to assess the importance of MGs that include multiple DERs and ESS. With the importance rank order list of the multiple MG networks, the core MG (or node) of power production and consumption can be identified. Identifying such an MG is useful in preventing cascading failures by distributing the concentration on the core node, while increasing the effective link connection of the energy flow and energy trade. This scheme can be applied to identify the most profitable MG in the energy trade market so that the deployment operation of the MG connection can be decided to increase the effectiveness of energy usages. By identifying the important MG nodes in the network, it can help improve the resilience and robustness of the power grid system against large-scale cascading failures and other unexpected events. The proposed algorithm can point out which MG node is important in the MGs power grid network and thus, it could prevent the cascading failure by distributing the important MG node's role to other MG nodes.

Keywords : Page Rank Algorithm, Energy Flow, Smargrid, Artificial Intelligence, Technology, Microgrid

Major Classification Code: Artificial Intelligence

1. Introduction

The concept of microgrids (MGs) and their applications are important issues. MGs are well known as a promising way to guarantee a reliable energy supply and meet the demand of users, such as prosumers and consumers. This can be achieved by aggregating conventional generators, renewable energy systems (RESs), and energy storage systems (ESSs) to form a flexible energy network. Photovoltaics (PVs) with solar power and wind power turbines (WTs) are commonly considered as RESs. With RESs and energy flow management, a smart microgrid can

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be defined and constructed. Also, an energy management system (EMS) plays an important role in an MG to operate its components and distributed energy resources (DERs) efficiently.

A microgrid is a small-scale energy system that can generate, store, and distribute electricity locally. Microgrids are gaining popularity due to their ability to operate independently from the main power grid, and their potential to integrate renewable energy sources. Efficient energy management is essential for the optimal operation and management of a microgrid. Energy flow control is a critical aspect of energy management in microgrids. Energy flow control involves managing the energy flow between the various components of the microgrid, such as generators, energy storage systems, and loads.

The PageRank algorithm is a popular algorithm used in web search engines to rank web pages based on their importance. The algorithm has also been used in network analysis to identify the important nodes in a network. In this paper, we propose a novel approach to energy flow control in microgrids using the PageRank algorithm. We adapt the PageRank algorithm to identify the critical nodes in the microgrid network, and control the energy flow accordingly.

Numerous studies have investigated the importance of power grid nodes using social network analysis and other methods based on network theory. These studies have focused on various aspects such as power flow and load capacity. However, there has been little research on the importance assessment of multiple MGs networks, which include DERs (or RESs) and ESS facilities. In this paper, we propose a comprehensive scheme for assessing the importance of such networks.

Multiple MGs networks are susceptible to cascading failure due to changes in weather and other unexpected reasons. A failure in one MG can trigger a series of failures, eventually leading to a blackout. Accurately identifying critical MG or DER nodes is crucial in preventing or forecasting blackouts.

2. Theoretical Background

Many studies have explored the significance of power grid nodes, represented as a network with nodes and edges. For instance, Watts and Strogatz (1998) analyzed the western US electrical power grid, while Xiao (2013) proposed a new multi-criteria method for measuring node importance. Other works such as [3], Panteli (2015), and Sun et al. (2021) evaluated the vulnerability of power systems based on various criteria, such as operating mode and line currents. Additionally, some researchers have examined the impact of fault chains on grid assessment (Ding, Guo, Zhang, et al., 2015; Wu, Liu, Gao, et al., 2020) and identified vulnerable power grid nodes using weighted networks (Zhang, Li, Zhu, et al., 2013; Li, Kang, Yu, et al., 2019). Moreover, Feng, Li, and Li (2020) suggested an improved PageRank algorithm to identify critical nodes in a power grid.

Although these methods are suitable for power grids, there has been limited research on methods and strategies for multiple MGs networks. Therefore, this paper proposes a modified PageRank algorithm to assess the importance of MGs that comprise multiple DERs and ESS. By ranking the importance of multiple MGs, the core MG (or node) of power production and consumption can be identified, which is essential for preventing cascading failures and optimizing energy usage.

3. Methodology

3.1. Modified Page Rank Algorithm

PageRank (denoted by PR) algorithm was proposed by Sergey Brin and Larry Page (1998), the founders of Google. This algorithm efficient identifies the most influencing webpage by the hyperlink structure of the web system. PR algorithm ranks high importance of a webpage. If a webpage has an important links to it, its links to other pages also become important. Moreover, based on complex network theory, PR algorithm has been widely applied in many fields, such as google search, literature quality evaluation and so on.

The web can be represented as a directed graph whose nodes correspond to webpages and edges correspond to the hyperlinks. The hyperlinks into a webpage are called in-links and point into nodes, and the in-degree of a webpage is equal to the number of its in-links. The hyperlinks that point from nodes are called out-links, and the out-degree of a webpage is equal to the number of its out-links. A webpage rank can be identified through the hyperlinks among different webpages. The essence of PR algorithm is that the rank of a webpage will be certainly high if the webpage is linked from a high-ranked one in Franceschet (2011).

The original PR value of a webpage is calculated as follows:

$$PR(u) = \frac{(1-\alpha)}{N} + \alpha \sum_{v \in D(u)} \frac{PR(v)}{D(v)} \qquad (1)$$

where N is the number of web pages in a web (in-links), $D(u)$ is the set of pages that point to page u, $PR(u)$ and $PR(v)$ are rank value of page u and v, respectively. $D(v)$ is the number of outgoing links (out-links) from page v. α is the damping factor normally set to 0.85, which mitigates the impact of random visiting and maintains the convergence of its iteration.

In order to fins $PR(u)$ in (1), the following iterative process is performed.

$$PR_{k+1}(u) = \frac{(1-\alpha)}{N} + \alpha \sum_{v \in D(u)} \frac{PR_k(v)}{D(v)} \tag{2}$$

3.2. Modified Page Rank Algorithm subject to Power Flow

Although the PR algorithm is simple and fast, the MG nodal load capacity also affects the importance of MG node in multiple MGs power grid network. Moreover, the MG's nodal load capacity will change distribution of power flow, some MG nodes may transmit more power than other MGs. The more power the MG node transmits, the more important the MG node is. Therefore, it is necessary to modify PR algorithm based on the direction and size of the MG's power flow.

Considering energy flow conditions and the weight contribution factor $w_k^{(v,u)}$, i.e., the importance from the MG incoming links and outgoing link, the modified PR can be written as

$$PR_{k+1}(u) = \frac{(1-\alpha)}{n} + \alpha \sum_{v \in D(u)} PR_k(v) w_k^{(v,u)}(v) \tag{3}$$

where $w_k^{(v,u)}$ is the energy importance weight which means energy node *v* contributes to node *u*. It is the same as $w_k^{(v,u)} = w_k(v \to u)$ and defined as follows

$$w_k^{(v,u)}(v) = \frac{\mathcal{E}(v)}{\sum_{v \in D(u)} \mathcal{E}(v)} \tag{4}$$

where $\mathcal{E}(v)$ is the energy flow that node *u* transmits it to the node *v*.

After calculating power flow of MG (power grid) nodes, the direction of power flow (transmission) lines is defined as the power flow direction. Therefore, a directed power flow line can be represented as a hyperlink. The directed power flow lines into a MG node represents the supply power to the MG node. The in-degree of a MG node is equal to the number of the directed power flow transmission lines from other MGs. So, the directed power flow line pointing from a MG node represents the power supplying node to them. The out-degree of a MG node is equal to the number of the directed power flow lines. Thus, we derive the comparison of internet and MG power grid topology as shown in Table 1.

The objective of this paper is to apply the PR algorithm to multiple MG network of power grid. Our proposed approach involves the following steps: 1) Model the microgrid network as a directed graph, where the nodes represent the various components of the microgrid, and the edges represent the energy flow between them. 2) Calculate the PageRank score for each node in the graph using the PageRank algorithm. 3) Identify the critical nodes in the microgrid network based on their PageRank score. 4) Control the energy flow between the critical nodes to optimize the performance of the microgrid.

Table 1: Comparison internet with power grid.

Network Graph Theory	Internet	MG Power Grid
Node	Web page	Bus or substation → Microgrid
Edge	Hyperlink	Power Flow with MG node
Information value (Structure of nodes)	Link relationship	Power flow
Degree	Visits of web page	Load capacity of MG (Importance of MG)
Initial quality of a node	Initial quality of a Web page	Importance of a MG nodal load

In such multiple MGs integrated power grid network, the importance of MG nodal load can affect the importance of whole MG network. The break down of the MG node with high importance results in high risk to the whole power grid network, compared to those MGs with relatively lower importance value. Therefore, the modified PR algorithm should provide a smart distribution to MG nodes with more important load rather than those with unimportant load.

If a MG node has higher importance, it means that MG has high capacity of power supply. Then, the energy consumers (or demanders) are likely to link this MG, since this MG offers a cheaper price deal to customer than other MG with low capacity. Every DER (consumer and prosumer) is likely to connect to this MG. Based on the Modified PR algorithm, the prosumers can find the best selection for profit.

4. Simulation and Discussion

4.1. Simulation Setup

The simulation model used in this paper is based on the Python programming tool. The microgrid power grid model is set up using the NetworkX library, which includes 20 microgrids (or nodes) that are connected through either a randomly connected link model or a pre-defined connected link model. Each microgrid node has a maximum power generation capability of 1 MW, with 10 distributed energy resources (DERs) connected to generate 100 kW.

The conceptual model of the multiple microgrids network considered in this paper is illustrated in Figure 1, where multiple DERs are connected to each microgrid.

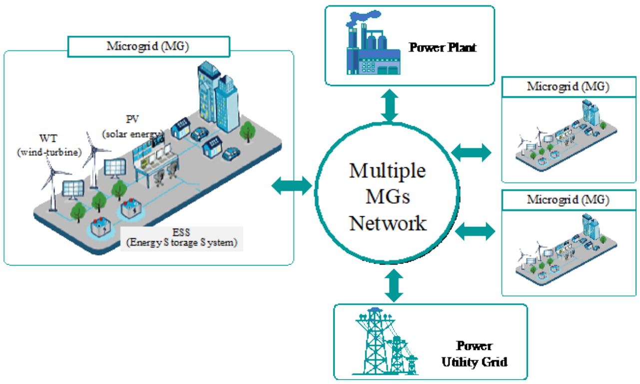

Figure 1: Conceptual Model of Multiple MGs Network Configuration in Smartgrid

4.2. Simulation Results

The process of modified PageRank algorithm is implemented as following:

Algorithm
Step 1: Specify MG node structure and input data
Step 2: Compute MG load flow calculation
Step 3: Compute adjacency Matrix, then specify the number of in-links and out-links of each MG node
Step 5: Assign energy flowed by as the weight contribution value of each branch
Step 4: Set the initial PR values
Step 6: Iterative calculation
Step 7: Find the converged PR values and verify the node's ranking values

Following the procedure of the algorithm, we set up the network model. First, the randomly connected MGs power grid network is set up as shown in Figure 2, and it is simulated according to PR algorithm assessment.

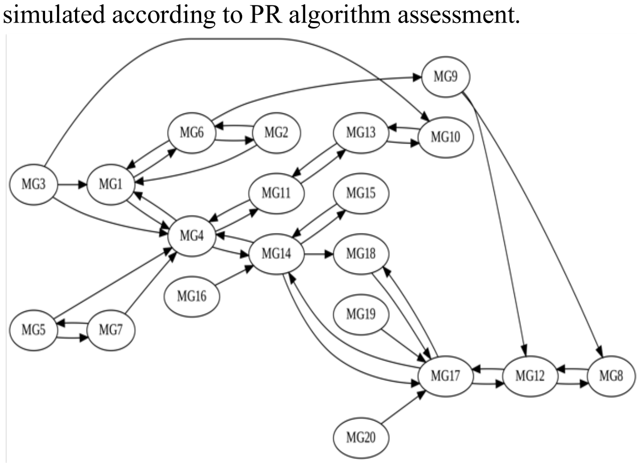

Figure 2: Randomly Deployed MGs Network with the Equal Power Flow

It is assumed in this study that the initial probability of each MG node is equal. The transition probability matrix is generated randomly using a uniform probability distribution function. After the PR algorithm converges, the ranking importance of each MG is determined and presented in Figure 3. The ranking of each MG may vary depending on the initial set-up and network topology, and the damping factor used in the PR algorithm is 0.85.

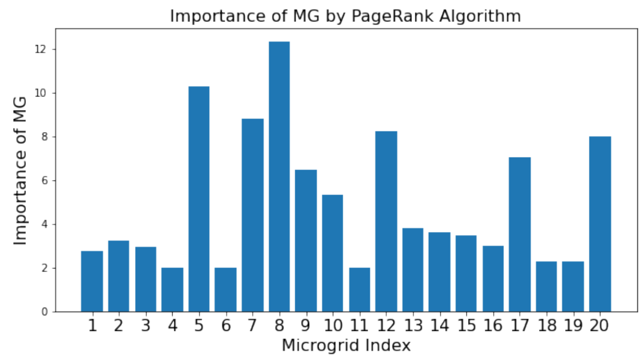

Figure 3: Result of Ranking Importance of MGs by PR algorithm for Randomly Deployed MGs Network

Figure 2 is one of the possible network topology scenarios. It should be noted that the MG with index-8 has the highest ranked importance value in this scenario. This indicates that the 8-MG node has higher power generation capability and then, the connected neighboring MGs are likely to rely on this MG node as a parent energy supplier. That is, the 12-MG node plays a critical role in the power generation and distribution process in this network. The importance ranking result in ascending MG order for this scenario are [3. 4. 3. 2. 11. 2. 9. 13. 7. 6. 2. 9. 4. 4. 4. 3. 8. 3. 3. 8.].

Secondly, the pre-defined network topology is simulated. The link connection and the initial weighting factor is pre-defined as shown in Figure 4.

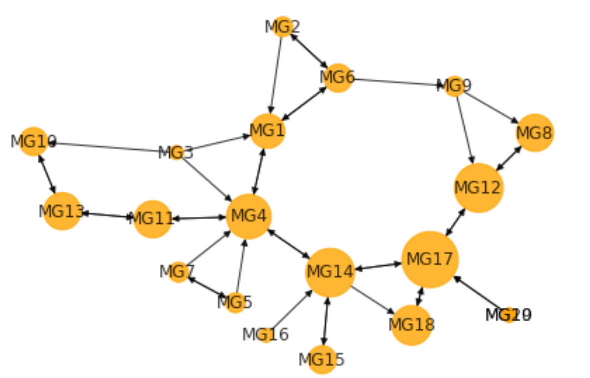

Figure 4: Pre-defined Deployed MGs Network with the Un-equal Power Flow

After simulation of PR algorithm, the ranking importance values are converged to [6. 2. 1. 10. 2. 4. 2. 7. 2. 4. 7. 12. 7. 12. 4. 1. 16. 8.1. 1.] as shown in Fig. 5. The result shown in Fig. 5 indicates that the outgoing edge of a MG node is weight on the basis of in-links and out-links as a power flow of a number to calculate the rank of MG node in MGs power grid network. The objective of the proposed algorithm is to maximize the power of a path to select the MG node indicating the highly ranked importance. As shown in Fig. 5, the 17-MG node has the highest rank value, which means that this MG node is most important in terms of energy supply chain.

The failure of this specific MG node would cause severe damage to the entire power grid network, leading to an energy blackout. Thus, the proposed algorithm and simulation model play a crucial role in identifying important MG nodes and evaluating the power grid network's vulnerability. These results must be considered when assessing power grid reliability and sustainability. Because of the unpredictable nature of severe weather, large-scale cascading failures are an inescapable reality in energy networks. Nevertheless, the proposed algorithm and approach offer valuable insights into the structural vulnerability of the energy network.

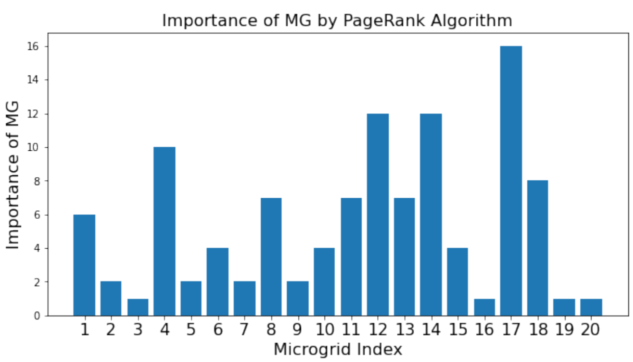

Figure 5: Result of Ranking Importance of MGs by PR algorithm for Pre-defined Deployed MGs Network

5. Conclusion

The proposed algorithm can also assist in designing efficient energy management and control strategies for the multiple MGs network. Moreover, it can be used in the planning and decision-making process for the expansion and upgrade of the power grid network. Furthermore, the proposed algorithm can be extended and applied to other types of networks with similar characteristics, such as communication and transportation networks. Thus, this paper demonstrates how to assess the reliability and vulnerability of the multiple MGs network by applying the modified PageRank algorithm. The considered MG network comprises multiple MGs with connected distributed energy resources and energy storage system facilities. Thanks to the proposed PR algorithm and procedure, it becomes possible to estimate or forecast the potential loss of the power grid network caused by large-scale cascading failures.

Overall, the proposed modified PageRank algorithm provides a useful and effective tool for assessing the reliability and vulnerability of the multiple MGs network. By identifying the important MG nodes in the network, it can help improve the resilience and robustness of the power grid system against large-scale cascading failures and other unexpected events. The proposed algorithm can point out which MG node is important in the MG power grid network. With the converged PR rank values of MG nodes, the assessment of the structural vulnerability of the energy network becomes more predictable. By identifying and measuring the importance of the multiple MGs network, the core MG node of power production and consumption can be identified. This result can eventually be utilized in preventing cascading failures by distributing the important MG node's role to other MG nodes, thus enabling the approximately maximum profit of the energy trade market to be obtained by distributing the energy flow.

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