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# Power Grid Partitioning Based on Functional Community Structure

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**ABSTRACT** Network partitioning is a popular research topic. Not all available partitioning methods are equally suitable for power grids. Community detection is a critical issue in complex network theory, and power grid is a typical type of complex network. This paper proposes a functional community structure based on an extended weighted network model. An extended adjacency matrix is used to represent an extended weighted complex network model based on coupling strength rather than the conventional adjacency matrix. Meanwhile, we upgraded the Newman fast algorithm of community detection for establishing a novel power grid partitioning algorithm. The electrical coupling strength (ECS) is defined to better reflect electrical characteristics between any two nodes in power grid. Modularity is also redefined as electrical modularity based on ECS. The Newman fast algorithm is upgraded with electrical modularity maximization as the objective to detect functional communities in power grids. A case study on IEEE test systems with 30, 39, 118, 300 buses and one Italian power network demonstrates the rationality of the extended weighted network model and partitioning algorithm.

**INDEX TERMS** Complex network, community detection, power grid partition, electrical coupling strength, Newman fast algorithm, functional community.

## I. INTRODUCTION

Reasonable partitioning is an important prerequisite for the effective operation and control of power grids. Analyses of large-scale power grid failure in recent years have shown that most accidents are caused by large-scale cascading, which is caused by overloading of the tie-line between grid divisions after a single component failure in the system. To this effect, system partition and tie-line security control play a crucial role in large grid operation control [1]. Traditionally, power grid partitioning was mainly based on the administrative region and long-term accumulation of operational experience [2]. Not all traditional partitioning methods accurately reflect the partitioning characteristics of the grid, and thus can threaten the safe operation of the grid [3]–[5].

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The purpose of power grid partitioning is to facilitate the operation, control, and management of a regional power grid. Engineers can equip smart power networks with self-healing capability to safeguard vulnerable operating conditions and prevent calamitous outages [6]. The self-healing power system is defined as a system with advanced metering and control technologies which can efficiently detect system faults and recover most electrical functionality when contingency events occur [7]. From the engineer's perspective, the optimum partitioning of a self-healing power grid efficiently and automatically reacts to disturbances and guides the system to the best possible state [8].

Existing algorithms may focus on the physical structure of power grid while neglecting its function [9], and thus fail to fully reflect the electrical characteristics of the grid. Hierarchical spectral clustering can be used for power grid partitioning [10], and the admittance and average power flow may serve as weights which reflect the static internal structure and dynamic characteristics of the system. This method is not particularly rational due to the mix of static structure and dynamic indexes as weights. In the multi-attribute partitioning method [11], the K-Means algorithm and evolutionary algorithm are combined to partition the power network while electrical distances, cluster numbers, and cluster sizes are taken into consideration. This partitioning method requires that the number and size of clusters be predefined, which affects self-adaptivity. J. Guo [12] proposed an approach based on spectral clustering, the goal of which object is to exploit a partitioning algorithm for minimal convergence time. The modularity $Q$ serves as a benchmark to evaluate the partitioning results, though $Q$ is not designed specifically for power systems and thus does not appropriately reflect the electrical characteristics of power grids. Because of the increasing complexity of community detection problems, evolutionary computation is applied to obtain high quality solutions with reduced runtime. In [13], [14], two genetic algorithms with modularity and modified genetic algorithm (MIGA) and generational genetic algorithm (GGA+), have been modified to solve community detection problems in power systems. Through analyzing the performance, the results show that genetic algorithms are fast and powerful methods to detect communities in large scale power networks.

Community detection methods are active in determining various types of community structure in complex networks, however, these community detection methods are mainly based on topological features of networks [15]. The Kernighan-Lin algorithm, for example, is often used alongside other technologies for network partitioning [15]. Another popular technique is the spectral bisection method [15], which is based on Laplace matrix properties. Partitioning clustering is also commonly used to find clusters in a set of data points; K-means clustering is a popular partitioning clustering algorithm [15]. These community detection methods are mainly based on the topological features of networks and do not consider the function of the community, despite its importance. Conventional community detection methods may, to this effect, be inherently disadvantageous. Community detection methods tailored to complex networks may also be applied to power networks. For example, the similarity index can be redesigned to measure the proximity between different nodes [16], but the power grid's electrical properties are still not considered.

Power grid partitioning is used to identify which parts of the grid have relative independence and autonomy in terms of their functionality, which are structurally fundamental. However, the definition of the original community structure is only based on the density in connection distribution. In this paper, we call this the "**topological community structure**". This paper proposes a new concept, "**functional community structure**", corresponding an optimum partitioning algorithm that identifies community structures from the perspective of network functionality. In conventional community detection methods, the Newman fast algorithm is typically used to partition unweighted networks [17], [18]. Newman and Girvan proposed the modularity $Q$ which quantitatively evaluates partitioning performance. Modularity can also be applied to weighted networks [19]. Newman's method is often considered a benchmark to evaluate power network partitioning [12], [16] wherein the community by line connection density among nodes is considered, but not the function of transmission between nodes. This paper proposes a novel partitioning algorithm which we established based on the Newman fast algorithm by considering the functionality of power grids. We also use coupling strength to indicate the transmission ability of certain physical quantities between node pairs in the system. An extended weighted network model is drawn based on the coupling strength between any nodes.

The main contributions of this paper are:

1) The extended weighted network model is accompanied by an extended adjacency matrix with all non-diagonal elements as non-zero.
2) ECS is proposed as the extended weight for power grids in the extended weighted network model.
3) The Newman fast algorithm is upgraded to include electrical modularity and to detect functional community structures for power grid partitioning.

The rest of this paper is organized as follows. Section II discusses the extended weighted network model and ECS concept. The upgraded Newman fast algorithm is presented in Section III. The rationality of the extended weighted network model and partitioning algorithm are demonstrated based on the results of the proposed partitioning method as-applied to IEEE-30, IEEE-39, IEEE-118, and IEEE-300 test systems as well as an existing Italian power network. Simulation results are provided in Section IV. Section V is a summary and conclusion.

## II. ELECTRICAL COUPLING STRENGTH

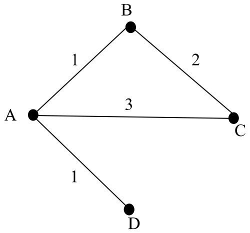
### A. EXTENDED WEIGHTED NETWORK MODEL

Many systems can be represented as a network or graph (e.g., the Internet, citation networks, social networks, biological and biochemical networks). The connection between nodes is usually represented in binary form; in other words, the network is represented by (0, 1) or binary matrices. The adjacency matrix $A_{ij}$ can be used to represent the network [19].

$$A_{ij} = \begin{cases} \mathbf{1}, & \textbf{if nodes } \boldsymbol{i} \textbf{ and } \boldsymbol{j} \textbf{ are connected} \\ \mathbf{0}, & \textbf{otherwise} \end{cases} \tag{1}$$

However, in fact, many networks are not unweighted. The connections in the network are not simply zero or one. A weighted network can be represented by an adjacency matrix with entries that are equal instead to the weights on the edges:

$$A_{ij} = \textbf{weigh of connection from } i \textbf{ to } j \tag{2}$$




$$A_{ij} = \begin{array}{cc} \begin{array}{cccc} A & B & C & D \end{array} & \\ \begin{pmatrix} 0 & 1 & 3 & 1 \\ 1 & 0 & 2 & 0 \\ 3 & 2 & 0 & 0 \\ 1 & 0 & 0 & 0 \end{pmatrix} & \begin{array}{c} A \\ B \\ C \\ D \end{array} \end{array}$$

In the above example, the adjacency matrix represents the connections in the left-hand figure. There is no direct connection between node C and node D, or nodes B and D, therefore, the weight between these two nodes is zero in the adjacency matrix. This conventional network model only indicates the connections among nodes and neglects the functional ability in transmission between nodes. In power or transportation networks, however, some physical quantities can still be transmitted between two nodes even if there is no direct connection between them.

The essential function of networks is to transmit physical or informational quantities between nodes; the previous definition of the adjacency matrix does not comprehensively reflect these features. Here, we establish an extended weighted network model which indicates the transmission ability between any two nodes. This functional ability is defined by coupling strength. The exact definition of "coupling strength" may differ for different types of networks with different functions. The previous definition of the adjacency matrix only considers weight of lines between nodes. Here, we update the adjacency matrix into an extended adjacency matrix wherein the element corresponding to two nodes is not the weight of the line between them, but the ability of transmission in terms of the coupling strength between them. The element corresponding to node C and node D in the former example is not zero. The extended adjacency matrix is written as follows:

$$EA_{ij} = \textbf{couplingstrength of connection from } i \textbf{ to } j \tag{3}$$

Coupling strength reflects the functional ability in transmission among any nodes whether they are directly or indirectly connected. The electrical coupling strength (ECS) for the power grid is defined below.

### B. ELECTRICAL COUPLING STRENGTH (ECS)

A power grid system is a typical complex network which contains nodes and links (i.e., buses and electrical transmission lines). ECS reflects the electrical characteristics of the grid during power transmission. Transmission ability between buses is defined by transmission capacity [20] and equivalent impedance [21] parameters which together define ECS. The ECS between buses $i$ and $j$ is:

$$\boldsymbol{E_{ij}} = \frac{\boldsymbol{C_{ij}}}{\boldsymbol{Z_{ij}}} \tag{4}$$

where $C_{ij}$ is the power transmission capacity when power is injected at bus $i$ and withdrawn at load bus $j$ [20]:

$$C_{ij} = min_{l\epsilon L}\left(\frac{P_l^{max}}{\left|f_l^{ij}\right|}\right) \tag{5}$$

where $f_l^{ij}$ is the power transfer distribution factor (PTDF) on line $l$ when a unit of power injected at bus $i$ and withdrawn from bus $j$; $P_l^{max}$ is the power flow limit about the transmission line $l$.

In Eq. 3, $Z_{ij}$ is the equivalent impedance between bus $i$ and $j$. Fig 1 shows the computation of equivalent impedance.

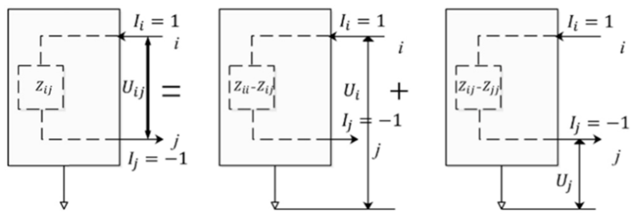



**FIGURE 1.** **Equivalent impedance computation scheme.**

The definition of the equivalent impedance is [21]:

$$Z_{ij}^e = z_{ii} - 2z_{ij} + z_{jj} \tag{6}$$

where $z_{ij}$ is the $i$th, $j$th element of the impedance matrix.

In Eq. 4, the scale of transmission capacity and equivalent impedance may be quite different so the ECS value may be more sensitive to one of them. To resolve this, the two quantities can be normalized as follows based on their average value:

$$\bar{C}_{ij} = \frac{C_{ij}}{\bar{C}} \tag{7}$$

$$\bar{Y}_{ij} = \frac{Y_{ij}}{\bar{Y}} = \frac{\frac{1}{Z_{ij}}}{\bar{Y}} \tag{8}$$

where $Y_{ij}$ is the reciprocal of $Z^e{}_{ij}$. $\bar{C}$ and $\bar{Y}$ are the average values of transmission capacity and equivalent admittance, respectively.

To adjust the influence of these two components, ECS can be further upgraded by changing their proportions as follows:

$$\bar{E}_{ij} = \left|\alpha \bar{Y}_{ij} + j\beta \bar{C}_{ij}\right| \tag{9}$$

where $\alpha$ and $\beta$ are proportion coefficients which together equal 1. The relationship of these two parameters is shown in Fig. 2.

### C. CONVENTIONAL ADJACENCY MATRIX VERSUS EXTENDED ADJACENCY MATRIX

This section compares the conventional adjacency matrix to the extended adjacency matrix. The value in Fig. 3 on the branch represents the admittance of each branch. Solid lines express the direct connection for each bus and dashed lines

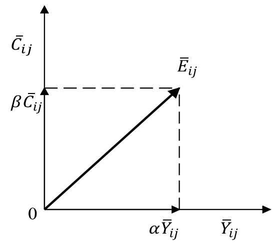



**FIGURE 2.** Different values describing composite weight index.

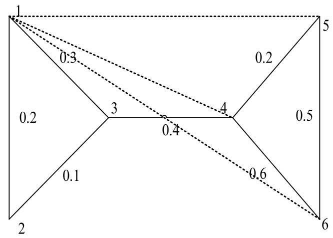



**FIGURE 3.** Network example.

are one instance of non-direct connection for bus 1. The adjacency matrix of the network shown in Fig. 3 is:

$$A_{ij} = \begin{bmatrix} 0 & 1 & 1 & 0 & 0 & 0 \\ 1 & 0 & 1 & 0 & 0 & 0 \\ 1 & 1 & 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 & 1 & 1 \\ 0 & 0 & 0 & 1 & 0 & 1 \\ 0 & 0 & 0 & 1 & 1 & 0 \end{bmatrix}$$

According to Eq. 9, the ECS matrix (extended adjacency matrix) with $\alpha$ and $\beta$ equal to 0.5 is as follows.

$$\bar{E}_{ij} = \begin{bmatrix} 0 & 1.22 & 1.24 & 0.48 & 0.45 & 0.44 \\ 1.22 & 0 & 1.76 & 0.50 & 0.46 & 0.44 \\ 1.24 & 1.76 & 0 & 0.54 & 0.48 & 0.45 \\ 0.48 & 0.50 & 0.54 & 0 & 0.96 & 0.86 \\ 0.45 & 0.46 & 0.48 & 0.96 & 0 & 0.81 \\ 0.44 & 0.44 & 0.45 & 0.86 & 0.81 & 0 \end{bmatrix}$$

The conventional adjacency matrix considers only direct connections and is unweighted. An ECS matrix (Eq. 9) encompasses the whole system – it includes directly connected and indirectly connected nodes altogether. For instance, in Fig. 3, there is no direct connection between bus 1 and bus 6. The element is equal to 0 between bus 1 and bus 6 in the conventional adjacency matrix, but in the ECS matrix, its weight is 0.44. The value of ECS for branches 1-2 and branches 1-3 is equal to 1.22 and 1.24, respectively, in the ECS matrix. In other words, the ECS matrix reveals relations among nodes from a new perspective.

## III. MODIFIED NEWMAN FAST PARTITIONING ALGORITHMS

### A. QUALITY FUNCTION: MODULARITY Q

Girvan and Newman proposed modularity $Q$ to measure the quality of partitioning in topological community detection [17]. If the topological community structure is well partitioned, the density of the internal connections is higher than the expected level of the random connection network [18].

Assume that the network has been divided into community structures, where $c_i$ and $c_j$ are the communities of vertex $i$ and $j$. The number of edges is equal to $m = \frac{1}{2}\sum_{ij} A_{ij}$ in the network. $k_i$ is the degree of the vertex $i$:

$$k_i = \sum\nolimits_{ij} A_{ij} \tag{10}$$

The expression of modularity $Q$ is:

$$Q = \frac{1}{2m}\sum\nolimits_{ij}\left[A_{ij} - \frac{k_i k_j}{2m}\right]\delta\left(c_i, c_j\right) \tag{11}$$

In the process of division of the community structure, the corresponding $Q$ value of each division is calculated as a series of modular values. The corresponding value of the peak division is determined as the best fit to the desired community structure division [18]. This Newman fast algorithm has significant disadvantages when utilized for functional community detection, as shown in Fig. 4, where solid lines express a direct connection for each bus and dashed lines are non-direct connections.

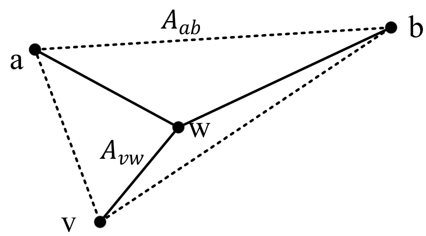



**FIGURE 4.** Functional community detection via Newman fast algorithm.

The Newman algorithm detects topological community structure according to density of connections. Our goal in conducting this study, however, was to detect functional community structure according to the density of coupling strength. The density of internal coupling strength in such a community is much higher than that among external nodes. Connections only exist for two nodes connected by a line, but coupling strength exists among all nodes. For instance, in the above figure, there is no direct connection between bus a and bus b; the element of conventional adjacency matrix $A_{ab}$ is equal to zero. Bus $v$ and bus $w$ have direct connection and a corresponding element $A_{vw}$. The coupling strength between bus $a$ and bus $b$ is $E_{ab}$, which is not zero. In addition, the magnitude of $E_{ab}$ is possibly higher than $E_{vw}$. In this study, we integrated the ECS and the Newman fast algorithm to detect functional community structures in power grids.

### B. PARTITIONING BASED ON ECS

The total electrical coupling strength of the whole power grid system is defined as follows:

$$\boldsymbol{M} = \frac{\mathbf{1}}{\mathbf{2}}\sum\nolimits_{ij} \boldsymbol{E_{ij}} \tag{12}$$

Because $E_{ij}$ is equal to $E_{ji}$, $M$ is equal to half of $\sum_{ij} E_{ij}$. We define the ECS value connecting bus $i$ as ECS degree $E_i$.

$$E_i = \sum_j E_{ij} \tag{13}$$

The electrical modularity $Q_e$ is:

$$Q_e = \frac{1}{2M} \sum_{ij} \left[ E_{ij} - \frac{E_i E_j}{2M} \right] \delta(c_i, c_j) \tag{14}$$

This equation can be rewritten as:

$$Q_e = \sum_{ij} \left[ \frac{E_{ij}}{2M} - \frac{E_i}{2M} \frac{E_j}{2M} \right] \delta(c_i, c_j) \tag{15}$$

If one unit of ECS is randomly obtained from a given power grid $\mathbf{Y}$, the probability of this ECS unit connecting bus $i$ to bus $j$ depends on the probabilities of two events.

- Event A: this unit of ECS is connected to bus $i$;
- Event B: this unit of ECS is connected to bus $j$.

The probability of event A is equal to $\frac{E_i}{2M}$. Because the ECS degree of $i$ is already known in the given network $\mathbf{Y}$, event B is not independent of event A. The probability of event B is equal to $\frac{E_{ij}}{E_i}$ because ECS $E_{ij}$ between $i$ and $j$ is already known in $\mathbf{Y}$. Therefore, the probability of this unit of ECS connecting from bus $i$ to bus $j$ should be $\frac{E_i}{2M} \cdot \frac{E_{ij}}{E_i} = \frac{E_{ij}}{2M}$.

Suppose a benchmark network $\mathbf{R}$ has the same value of the number of buses and the total ECS M as power network $\boldsymbol{Y}$. The ECS degree for any bus is the same as $\boldsymbol{Y}$, but the distribution of ECS is random. If we randomly select one unit of ECS from $\mathbf{R}$, the probability of event A is still equal to $\frac{E_i}{2M}$. The distribution of ECS is random in $\mathbf{R}$ ($E_{ij}$ is unknown), so events A and B are independent. The probability of event B is equal to $\frac{E_j}{2M}$. Therefore, the probability of this unit of ECS connecting from bus $i$ to bus $j$ is $\frac{E_i}{2M} \cdot \frac{E_j}{2M}$. The optimal partitioning result can be confirmed by searching the maximum value of electrical modularity $Q_e$. The network partitioning process is discussed in detail in the following section.

### C. MODIFY NEWMAN FAST ALGORITHM FOR ECS COMMUNITY DETECTION

The Newman fast algorithm was redesigned as Eq. 15. For a power network with N buses, the algorithm is implemented in the following steps.

*Step 1:* Initialization: there are N communities for the initialized power grid, which means each bus is a community. The electrical modularity $Q_e$ is calculated based on the ECS matrix.

*Step 2:* The extended adjacency matrix does not reflect whether nodes are directly connected, so the conventional adjacency matrix is used to judge direct connections. In this step, at first, determining whether there is direct connection between two communities through the adjacency matrix $A_{ij}$. Two communities which have at least one direct connection are grouped randomly. Figure 5 shows an illustration of this step. If Community 1 and Community 2 are merged into a single community, the prerequisite condition is that there must be at least one direct connection between them. However, there is no direct connection between Community 1 and Community 3, which cannot be partitioned in one community. This cannot be judged by the extended adjacency matrix because element between any nodes is non-zero, so the conventional adjacency matrix must be applied. The purpose of this step is to avoid grouping any two communities with no connection.

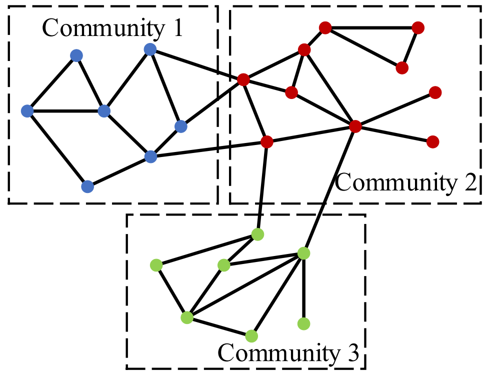



**FIGURE 5. Step 2 of proposed algorithm.**

*Step 3:* Increments of electrical modularity $Q_e$ are calculated as $\Delta Q_e$ when communities $v$ and $w$ are merged [16]. The calculation of the original $\Delta Q$ is based on the adjacency matrix, which does not reflect the electrical characteristics of power grids. ECS is used as weight to redefine the increments of electrical modularity:

$$\begin{aligned} \Delta Q_e &= 2 * \left(e^e_{vw} - a^e_v a^e_w\right) \\ e^e_{vw} &= \frac{1}{2M} \sum_{ij} E_{ij} \delta(c_i, v)\, \delta(c_j, w) \\ a^e_v &= \frac{1}{2M} \sum_i E_i \delta(c_i, v) \\ a^e_W &= \frac{1}{2M} \sum_j E_j \delta(c_j, w) \end{aligned} \tag{16}$$

Each merge then makes $\Delta Q_e$ increase in the maximum direction. The electrical modularity is recalculated as $Q_e$ by Eq. 15.

*Step 4:* Repeat Steps 2 and 3 to merge the communities until the whole network forms one community. The maximum number of mergers is N-1.

*Step 5:* Analyze and compare the partitioning results to determine the appropriate number of power networks.

A flowchart of the partitioning algorithm is shown in Fig 6.

## IV. CASE STUDY

We applied the proposed partitioning method to IEEE-30, IEEE-39, IEEE-118, and IEEE-300 test systems as well as one Italian power network, then compared the power grid partitioning results of different methods to determine the effectiveness of the proposed method. The proportion coefficients $\alpha$ and $\beta$ are equal to 0.5 (Transmission capacity and equivalent impedance have the same proportion in ECS). All the experiments were operated in MATLAB.

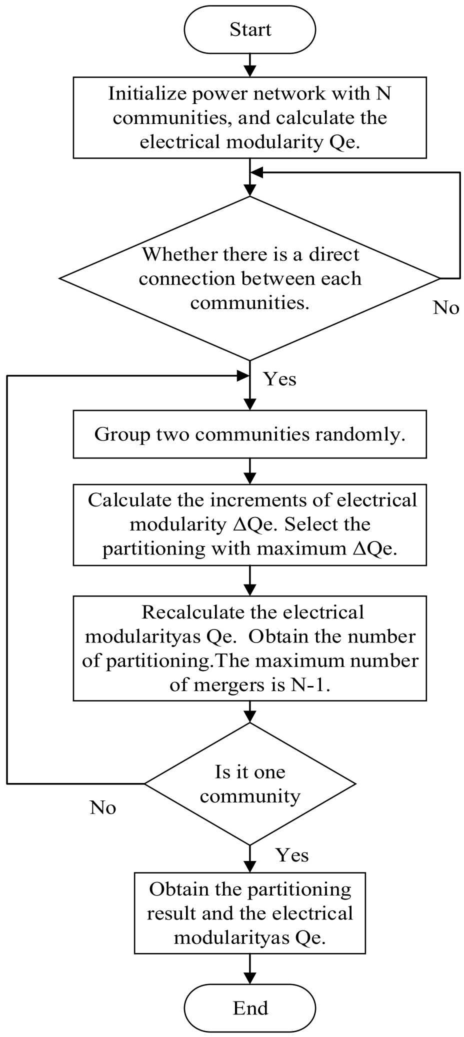



**FIGURE 6.** Modified Newman fast algorithm process.

## A. DIFFERENT TEST SYSTEMS

The modified Newman fast algorithm was applied to different test systems to obtain the electrical modularity values shown in Fig. 7a.

In Fig. 7a, the maximum value of electrical modularity is 0.06518 when the system is divided into three communities. The specific partitioning results are shown in Table. 1.

**TABLE 1.** IEEE 30-bus system partitioning results.

| | Bus number |
|---|---|
| Community 1 | 1-8, 28 |
| Community 2 | 12-17, 23-27, 29-30 |
| Community 3 | 9-11, 18-22 |

The community structure detected in the IEEE 30-bus power grid is shown in Fig. 8.

The curve in Fig. 7b is the value of electrical modularity with the modified Newman fast algorithm for the IEEE 118-bus system. The optimal partitioning result for IEEE 118-bus

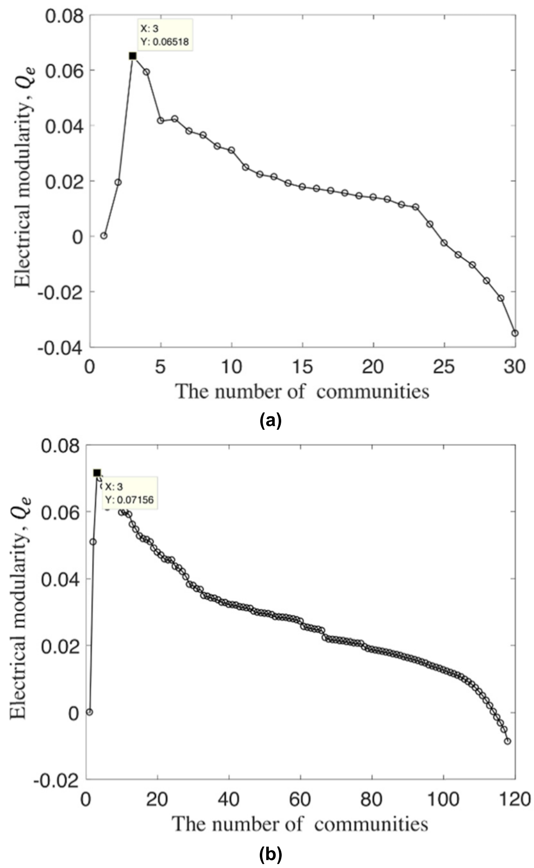



**FIGURE 7.** Electrical modularity values with modified Newman fast algorithm (a) IEEE 30-bus systems; (b) IEEE 118-bus systems.

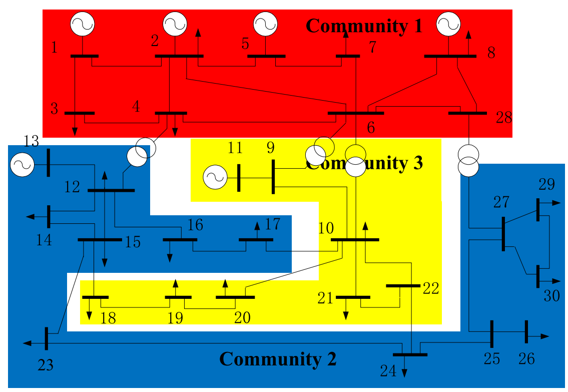



**FIGURE 8.** Three communities discovered in IEEE 30-bus standard power grid.

is three communities when the maximum value of electrical modularity $Q_e$ is 0.07156. The corresponding partitioning results are shown in Table 2.

The community structure is shown in Fig. 9, where three different colors are used to indicate three respective communities. There is a direct connection between node 8 and node 30 and between node 30 and node 38 in community 2, i.e., this community is not separated.

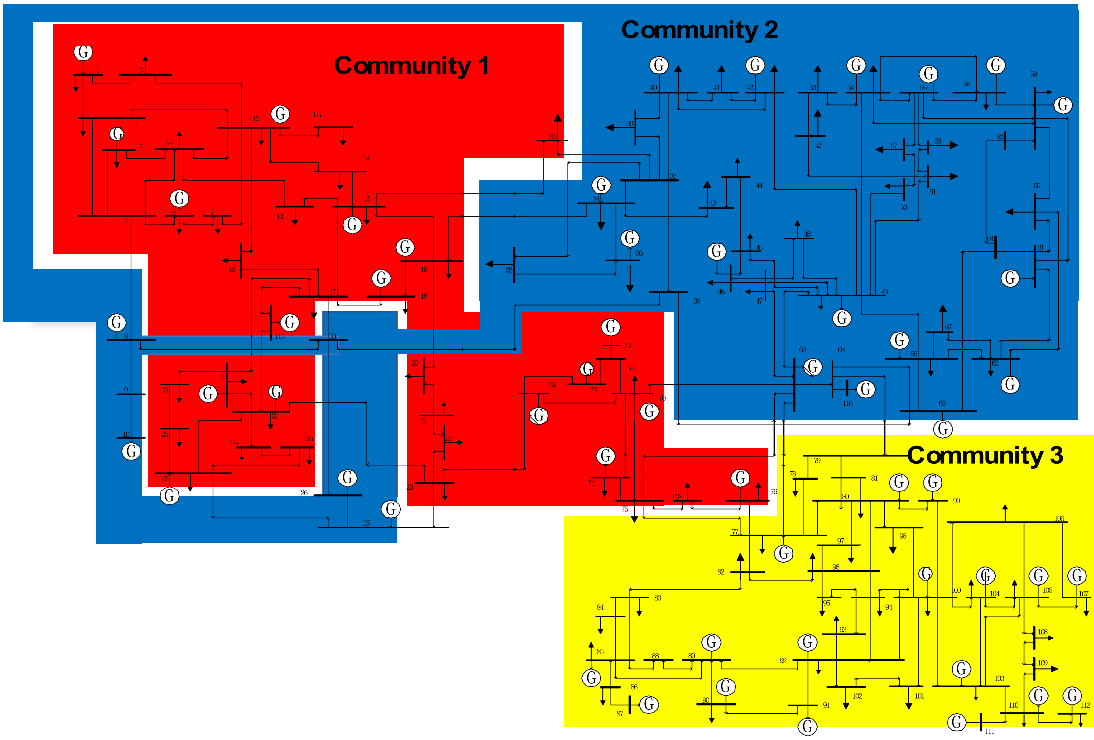



**FIGURE 9.** Partitioning results for IEEE 118-bus system.

**TABLE 2.** IEEE 118-bus system partitioning results.

| | Bus number |
|---|---|
| Community 1 | 1-7, 11-24, 27-29, 31-33, 70-76, 113-115, 117, 118 |
| Community 2 | 8-10, 25, 26, 30, 34-69, 116 |
| Community 3 | 77-112 |

To determine the feasibility of the proposed algorithm as-applied to large-scale power grid systems, we tested it on the IEEE 300-bus and an existing Italian power network. The optimal partitioning results for the IEEE 300-bus are a division into five communities with electrical modularity equal to 0.08778. The Italian power network includes 521 buses, 159 generators, and 679 branches. The best partitioning result is 7 clusters with maximum electrical modularity of 0.1299. Fig. 10 shows the electrical modularity with the modified Newman fast algorithm for both networks. Table.3 shows the number of bus and branch in each community for Italian power network.

### B. COMPARISON AGAINST ORIGINAL NEWMAN FAST

We compared the modified Newman fast algorithm with the original algorithm on the IEEE 30-bus system and IEEE 118-bus system per the resulting topological community and functional community structures. The original Newman fast algorithm as-applied to the IEEE 30-bus system produced the modularity and community number curve shown in Fig. 11.

**TABLE 3.** Italian power network partitioning results.

| | The number of buses | The number of branches |
|---|---|---|
| Community 1 | 73 | 84 |
| Community 2 | 94 | 102 |
| Community 3 | 100 | 119 |
| Community 4 | 71 | 84 |
| Community 5 | 49 | 52 |
| Community 6 | 44 | 48 |
| Community 7 | 90 | 107 |

As shown in Fig. 11, the optimal partitioning result is 4 communities when the maximum modularity is 0.5434. The definitions of modularity between the two methods we tested here are entirely different, so directly comparing their values is not meaningful – the proposed electrical modularity better indicates network functionality. We compared the two partitioning results instead by upgraded modularity $Q_e$. The partitioning result obtained by the original Newman fast algorithm was evaluated by the upgraded modularity and compared to the modified Newman fast algorithm as shown in Table. 1.

Table. 4 is a comparison between the two algorithms, where the partitioning result generated by the modified Newman fast algorithm is better.

The same verification method was applied to the IEEE 118-bus system. The optimal partitioning result by the original Newman fast algorithm is 11 communities. Table. 5

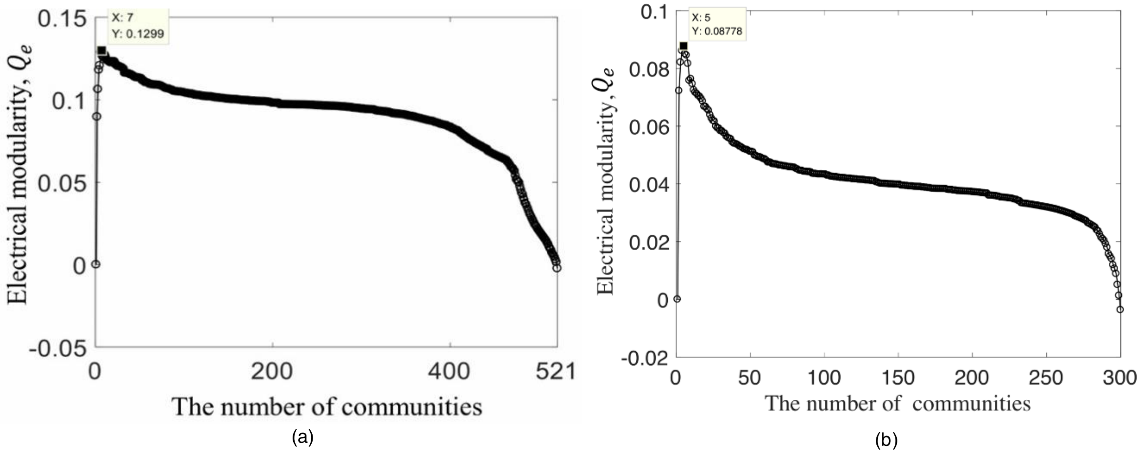



**FIGURE 10.** Electrical modularity values with modified Newman fast algorithm (a) Italian power network; (b) IEEE 300-bus system.

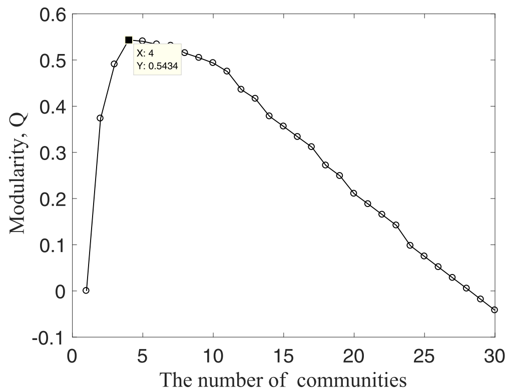



**FIGURE 11.** Modularity with original Newman fast algorithm for IEEE 30-bus system.

**TABLE 4.** Comparison between algorithms for IEEE 30-bus system.

| | The number of communities | Electrical modularity $Q_e$ |
|---|---|---|
| Modified Newman fast algorithm | 3 | 0.0652 |
| Original Newman fast algorithm | 4 | 0.0640 |

**TABLE 5.** Comparison between algorithms for IEEE 118-bus system.

| | The number of communities | Electrical modularity $Q_e$ |
|---|---|---|
| Modified Newman fast algorithm | 3 | 0.0716 |
| Original Newman fast algorithm | 11 | 0.0684 |

shows this partitioning result as evaluated by electrical modularity $Q_e$, which is lower than that of the proposed algorithm.

### C. COMPARISON AGAINST PREVIOUS POWER GRID PARTITIONIGN METHODS

We compared the modified Newman fast algorithm against previously published methods to further assess its performance. In one such previous study [16], similarity was defined to measure the proximity between different nodes based on adjacency matrix $A_{ij}$. The similarity neglects electrical properties, which is unweighted and undirected. The IEEE 39- bus and IEEE 118-bus system served as test systems [16], so we use them again here to make comparisons in terms of the upgraded modularity.

The curve of the relationship between electrical modularity and the number of communities in the IEEE 39-bus system is shown in Fig. 12. The maximum value of electrical modularity is 0.07076 when the network is divided into three communities.

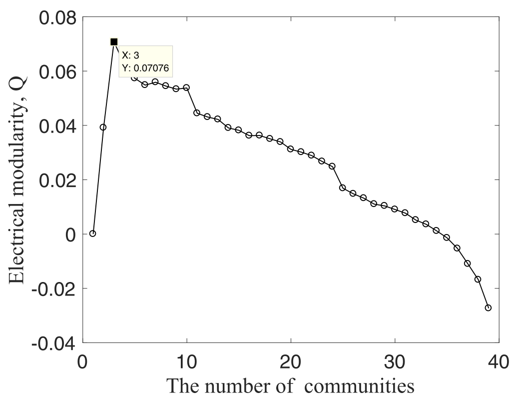



**FIGURE 12.** Electrical modularity with modified Newman fast algorithm for IEEE 39-bus system.

In the reference study [16], the IEEE 39-bus system was divided into five communities based on similarity and the partitioning results were as shown in Fig. 13(b). The corresponding electrical modularity of this result is 0.0617, which is smaller than 0.07076. This suggests that the performance of the modified Newman fast algorithm is better in regard to detecting functional communities.

The optimal partitioning results for these two methods are shown in Fig. 13. Table. 6 lists ECS values for certain buses which differed in these two sets of partitioning results.

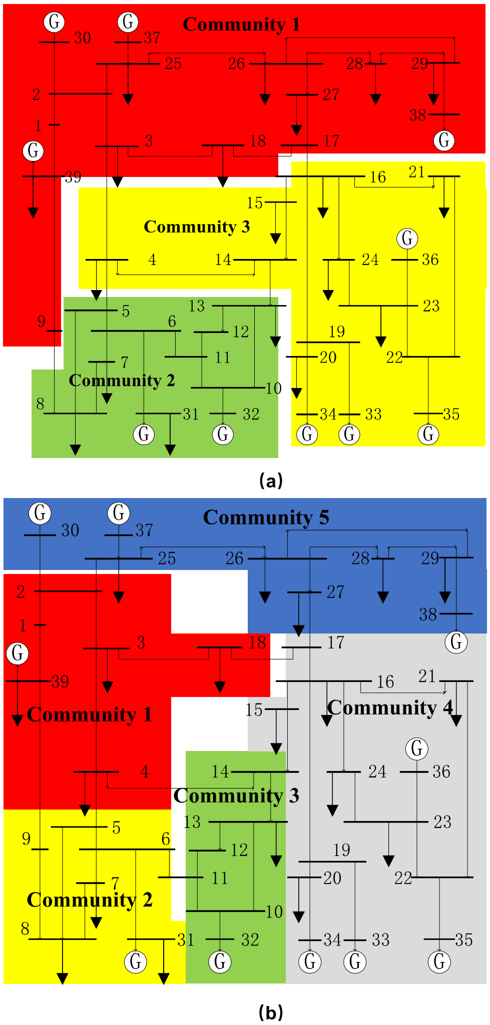



**FIGURE 13.** Partitioning results on IEEE 39-bus (a) modified Newman fast algorithm ($Q_e$ï£i = 0.07076); (b) The method in [16] ($Q_e$ï£i = 0.0617).

**TABLE 6.** Comparison between algorithms for IEEE 118-bus system.

| From bus | To bus | Electrical coupling Strength (ECS) |
|---|---|---|
| 3 | 4 | 1.263 |
| 4 | 14 | 2.010 |
| 8 | 9 | 0.779 |
| 9 | 39 | 0.917 |
| 17 | 18 | 2.412 |
| 16 | 17 | 2.156 |

For instance, bus 4 and bus 14 are partitioned in one community by the modified Newman fast algorithm but placed into the same community but different clusters by the other method [16]. The ECS of branches 3-4 is also smaller than that of branches 4-14. A greater ECS between two nodes indicates stronger correlation between two points and greater likelihood that the nodes are to be switched to the same community.

**TABLE 7.** Different partitioning results for IEEE 118-bus in [12].

| Partition | Areas |
|---|---|
| OP 1 | Community 1: 1-43, 72, 113-115, 117;<br>Community 2: 44-71, 73-112, 116, 118 |
| OP 2 | Community 1: 1-41, 43, 72, 113-115, 117;<br>Community 2: 42, 44-71, 73-112, 116, 118 |
| OP 3 | Community 1: 1-68, 72, 113-117;<br>Community 2: 68-71, 73-112, 118 |

Furthermore, the IEEE 118-bus system is divided into eight communities in [16]. To compare with our partitioning algorithm, we used electrical modularity to compare two partitioning results based on modified Newman fast algorithm and the method in [16]. The $Q_e$ for the modified Newman fast algorithm is equal to 0.0716 when the system is divided into three communities. For the method in [16], the $Q_e$ is 0.0698 when the system is divided into eight communities. It is obvious to find that electrical modularity of our partitioning result is larger than the other one. For further investigation, a comparison is made between our method and the method in the literature [12]. The approach is based on spectral clustering. There are three optimal partitioning results for IEEE 118-bus system in [12].

In another previous study [12], coupling parameters are used to evaluate the performance of the partitioning results listed in Table. 7. Through comparison, OP1 has a better partition [12]. Modularity was also used in previous studies as a benchmark to evaluate the performance of other partitioning results [10], [12]. However, the original modularity is not designed for power systems and does not reflect the functionality of power grids. Electrical modularity $Q_e$ is a better benchmark to evaluate partitioning results for power systems. Three partitioning results in Table. 7 are evaluated by electrical modularity $Q_e$, which are respectively equal to 0.0719, 0.0710, and 0.0597. A greater electrical modularity indicates favorable partitions. The electrical modularity of OP1 is greater than the electrical modularity of OP2 and OP3, which is similar to previously published results [12]. Further, as shown in Table 4, the electrical modularity detected by the modified Newman fast algorithm is 0.07156 which is very close to the electrical modularity of OP1.

### D. POWER FLOW ANALYSIS

To further demonstrate the rationality of the proposed algorithm in this paper, a power system simulation package (MATPOWER) is applied to achieve the boundary power flow between each community. For better power grid partitioning, it should have lower boundary power flow relative to the whole network load. To reflect this characteristic, we proposed Boundary Power Flow Factor (BPFF), which is defined as:

$$BPFF = \frac{\sum_{vw} |P_{vw}|}{\sum_i L_i} \tag{17}$$

**TABLE 8.** Boundary power flow of IEEE-118 bus system.

| Boundary | Power flow (MW) | Boundary | Power flow (MW) |
|---|---|---|---|
| 5-8 | 337.53 | 33-37 | 11.90 |
| 15-33 | 11.10 | 68-81 | 57.23 |
| 17-30 | 229.10 | 69-70 | 92.28 |
| 19-20 | 10.75 | 69-75 | 96.37 |
| 19-34 | 0.20 | 69-77 | 40.42 |
| 23-25 | 169.47 | 75-77 | 38.39 |
| 25-27 | 169.47 | 76-77 | 64.80 |

where, $v$ and $w$ are nodes in different communities; $P_{vw}$ is boundary power flow between bus $v$ and bus $w$; $L_i$ is the load in bus $i$. Lower value of BPFF means the partitioning results representing stronger internal power supply and weaker external interaction.

According to the previous discussion, IEEE-118 bus system is partitioned as three communities based on the modified Newman algorithm. Fig. 9 is the partitioning results, in which different colors represent different communities. Table. 8 is the boundary power flow of the partitioning results for IEEE-118 bus system based on the proposed algorithm.

The BPFF of this partitioning result is equal to 0.3415. Afterwards, we calculated the BPFF of partitioning result in [16]. The value of BPFF is equal to 0.3794, which result is larger than the partitioning result obtained by the proposed algorithm. To further verify and compare the proposed partitioning algorithm, we calculated the BPFF of IEEE-39 bus system in [16]. In literature [16], the IEEE-39 bus system is partitioned as 5 communities with BPFF as 0.2127. Subsequently, in this paper, considering the electrical characteristic of power network and interaction between all buses, the corresponding BPFF of partitioning result is 0.1264, which is much smaller than 0.2127. Similar with the results obtained by IEEE-118 bus system, it proves that the modified Newman partitioning algorithm proposed in this paper can more reasonably and accurately partition the power network compared with the previous studies.

## V. CONCLUSION

Reasonable partitioning is crucial for successful power grid operation and control. There are many existing techniques for grid partitioning, but not all apply directly to power systems. This paper proposed a power grid partitioning method which works by detecting functional community structures from the complex network perspective. An extended weighted network model is first established based on the extended adjacency matrix, wherein elements corresponding to node pair transmission ability are defined according to coupling strength. The coupling strength is not only applicable to power network partitioning. The coupling strength of different networks has their specific definitions. The electrical coupling strength for the power grid is then determined and integrated with the Newman fast algorithm, then electrical modularity $Q_e$ is defined to evaluate the power grid partitioning performance. We found that the extended adjacency matrix reveals relations among nodes from a new perspective. Our partitioning method performed well by comparison against other methods. Our results show that electrical modularity $Q_e$ can replace modularity as an effective benchmark for power grid partitioning results.

For the future work, we plan to test our partitioning method on distribution networks to identify community boundaries. A distributed generator (DG) can be allocated for different communities based on these results. We also plan to use a genetic algorithm to optimize the DG site, DG number, DG capacity, and DG type.

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