Understanding Communities from a New Functional Perspective in Power Grids

Xiaoliang Wang, Fei Xue, Shaofeng Lu, Lin Jiang, Ettore Bompard, Marcelo Masera

***Abstract*— The contributions of this paper include a new concept, a new question and a new method. This paper proposes the concept of functional community, which is different from conventional topological community. Functional community is defined with two meanings: (1) tighter internal coupling for better efficiency within the same community; (2) more internal transmission from source to sink nodes within the same community. Then a new question about how to detect functional communities in power grids is analyzed, and most existing algorithms are not applicable. Therefore, a new method is put forward. Corresponding to meaning 1, Electrical Coupling Strength (ECS) is defined to replace conventional adjacency matrix; corresponding to meaning 2, Power Supply Strength (PSS) is defined and integrated with ECS to form the newly defined Electrical Functional Strength (EFS). Based on these two changes, we apply the proposed power supply modularity as a benchmark to evaluate any partitioning of power grids. Moreover, the Newman fast algorithm is modified with power supply modularity maximization to detect functional communities in power grids. The capability of the proposed partitioning method is demonstrated via the IEEE-118, IEEE-300 bus systems, and an Italian power grid. We argue that the conventional topological modularity may exaggerate the community characteristics of power grids and is inferior to the power supply modularity in detecting some functional features in communities. The work can also give inspirations to other engineering networks for functional communities.**

Index Terms— Complex network; Community detection; Functional community; Power grids partitioning; Power supply modularity

I. INTRODUCTION

As power systems continue to thrive, the scale of topology in power networks keeps increasing. The structural functions and characteristics of power grids are becoming more and more complicated. The ever-increasing complexities of power systems make power networks more unstable and vulnerable to cascading failures, equipment outages, and voltage collapse [1], [2].

An appropriate network partitioning will result in a flexible, manageable and adaptive distributed control strategy that can be utilized to detect an islanding approach to prevent the diffusion of large-scale power failures [3]. Furthermore, a suitable power grid partitioning strategy will prevent cascading failures resulting in significant blackouts [4]. Additionally, power network partitioning can be applied to determine the necessary management of the power systems after a blackout to accelerate the system restoration process [5].

Community structure represents the composition and inter-relationship of a network community and is one of the most significant features of complex networks [6], [7]. In complex network theory, community detection, essentially a clustering problem, can be applied to understand the structural characteristics of networks [8]. Some studies focus on the clustering of load to provide enhanced knowledge on the nature of the consumption and assist meaningful customer grouping [9], [10]. However, this load characteristics clustering is a different topic from network partitioning. A large number of algorithms have been proposed to detect communities in complex networks. The Kernighan-Lin algorithm was proposed by randomly partitioning the network into two subnetworks and exchanging the nodes among subnetworks to detect the communities [11]. In [12], Mahmood *et al*. presented a new spectral clustering algorithm using sparse linear coding. Recently, Ni *et al*. [13] proposed a spectral clustering community detection algorithm that combined the multi-similarity method and K-means clustering algorithm. In [14], Liu *et al*. presented the weighted NWBBO algorithm that aimed at the problem that the global topology of the biogeography-based optimization (BBO) algorithm causes a large amount of calculation based on small-world topology. The power flow is utilized as the weight to establish a weighted undirected network model. Community detection methods can be applied to power networks as a complement to conventional power grid partitioning methods. Newman has proposed a community detection method using an adjacency matrix and modularity Q [15]-[17]. Some researches on power grid partitioning have

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utilized different community detection methods, but all use modularity Q to quantitatively evaluate partitioning performance [18]-[20]. However, these early studies simplified power grid models, neglecting the complex electrical properties and the functionality of power networks. Moreover, the definition of conventional modularity is not designed specifically for power systems and therefore does not appropriately reflect their electrical characteristics.

The contributions of this paper include a new concept, a new question and a new method. In this work, communities analyzed in most existing studies are summarized as **topological communities**. This paper proposes a new concept of **functional communities** considering the functionalities of engineering networks. Then a question about how to detect functional communities in power grids is asked. Most existing partitioning methods are proved not applicable for this question. Furthermore, a new method based on extended adjacency matrix and modified Newman fast algorithm is introduced as a solution for this question. To our best knowledge, no previous works have identified the engineering and functional characteristics of communities in this paper. The target of this paper is not only to solve power grids partitioning problem, but also to explore new characteristics in complex networks. Functional community itself is also an innovative concept in complex networks. This is promising to be extended to other engineering networks, such as transportation networks, gas-supply networks and water-supply networks. This could be a contribution in complex network theory.

The rest of this paper is organized as follows. Section II defines and discusses the concept of functional communities in power grids. In Section III, we describe the conventional modularity and redefined power supply modularity. Then, an optimum partitioning algorithm is proposed in Section IV. To demonstrate the rationality of the proposed partitioning algorithm and metrics, Section V describes the experimental results by the IEEE-118, IEEE-300 bus systems, and an Italian power grid. Finally, Section VI presents conclusions.

II. Functional communities in power grids

A. From topological communities to functional communities

Although communities were widely studied for network models of different fields and systems, there is no standard definition of communities universally accepted. Community is more like a perceptual impression as some subsets of nodes highly linked among themselves but loosely connected to the rest of the network. However, different algorithms may understand and quantitatively evaluate "highly linked" by different methods. Table I is a summary of some most typical definitions of communities.

In Table I, although different definitions utilize different parameters to depict communities, all these basic parameters (i.e. number and distribution of links, number and degree of nodes, distance of path, Laplacian matrix and adjacency matrix) only characterize **topological** features of networks. Similarity is measured by the distance between a pair of vertices [5], but it depends on how this distance is defined. Currently, most existing definitions for this distance are still based on topological features [5]. Therefore, all these communities are summarized as **topological communities** in this paper.

TABLE I
Comparison about different definitions of communities

Defining Method	Main Idea	Basic Parameters
Density [5]	Intra link density should be higher than average density.	Number of links and nodes
Connectedness [5]	There must be a path between each pair of its vertices, running only through limited vertices.	Distance of path
Modularity [5]	Probability of intra link distribution is higher than random connection.	Probability of link distribution
Spectral [5]	To infer structural relationships between vertices from the similarity of the corresponding components of eigenvectors of special graph matrices.	Laplacian matrix or adjacency matrix
Similarity [5]	Communities are groups of vertices similar to each other.	Distance between a pair of vertices.
Degree [6]	The sum of degrees within the community is larger than the sum of degrees toward the rest of the network.	Degree
LS-set [6]	A set of nodes such that each of its proper subsets has more ties to its complement within the set than outside.	Degree and link distribution
k-core [6]	A subgraph in which each node is adjacent to at least a minimum number of the other nodes in the subgraph.	Link distribution

In the engineering field, the purpose of network system community detection is to investigate and enhance network functionality by understanding community structure. Different network systems may have different functionalities and physical rules, for example, in [21], [22], Wang *et al*. presented a methodological framework to study the robustness of the power network from both structural and functional perspectives, so **non-topological features** may play essential roles in detecting functional communities. A typical functionality of engineering networks is to transmit physical elements, in this context, a community has two layers of meaning from the perspective of functionality as

1) Tighter internal coupling: Within the same community, physical elements are transmitted through paths with greater efficiency than between different communities.
2) More internal transmission: There is more transmission of physical elements from source to sink nodes within the same community than between communities.

Based on our previous preliminary studies [25][28], in this paper, we propose **a comprehensive concept** of **functional community** to characterize this perspective of engineering functionality. For meaning 1, the efficiency and ability of transmission may greatly depend on the physical capacities of components and rules of flow distribution which cannot be fully represented by topological parameters in Table I. For meaning 2, nodes in engineering networks may have different types, such as source, sink and transmission nodes [23]. None of the

definitions in Table I has considered the source-sink relations or node type distribution [23] in communities.

Then following the above discussion about power grids partitioning, **a new question** could be naturally asked: **how to detect functional communities in power grids**? In power grids, the meaning 1 could correspond to less internal power losses and less change of power flow on external lines caused by change in intra-zone transactions [24]. Meaning 2 could reflect more power supply within zones and less power flow on the zone's boundaries (less inter-zone transmission). Most existing methods for topological communities are based on a conventional adjacency matrix and cannot characterize the physical features in meaning 1. None of them can reflect the source-sink relation in meaning 2. In the following sections, a new method based on a new adjacency matrix model and a new algorithm will be introduced as **a new solution** for this question.

B. Electrical coupling strength and power supply strength

In complex network theory, the adjacency matrix A_{ij} is widely applied to represent the connection relationship between nodes in network topology[15], [16]. This is characterized as

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

The adjacency matrix A_{ij} only indicates the connection between directly connected nodes and neglects the functionality of transmission among nodes. Nevertheless, in power networks, some physical elements can still be transmitted between two nodes even if there is no direct connection between them. Consequently, ECS was defined in our previous study [25], whether they are directly or indirectly connected, by combining electrical distance (equivalent impedance) [26] and transmission capacity [27]. The ECS between bus v and bus w is defined as

$$\overline{E}_{vw} = \left| w\overline{Y}_{vw} + jx\overline{C}_{vw} \right|. \tag{2}$$

To balance the effect caused by the different scales of Y_{vw} and C_{vw}, we normalize these two parameters based on their average value as

$$\overline{Y}_{vw} = \frac{Y_{vw}}{\overline{Y}} = \frac{\frac{1}{Z^E_{vw}}}{\overline{Y}}, \tag{3}$$

$$\overline{C}_{vw} = \frac{C_{vw}}{\overline{C}}, \tag{4}$$

where $\overline{Y}$ and $\overline{C}$ are the average values of equivalent admittance and transmission capacity in the whole network. Y_{vw} is the reciprocal of Z^E_{vw} that is the electrical distance between bus v and bus w [26], which is defined as

$$Z^E_{vw} = z_{vv} - 2z_{vw} + z_{ww}, \tag{5}$$

where z_{vv} (z_{vw}, z_{ww}) are corresponding elements in the impedance matrix of the network.

In (2), C_{vw} is the power transmission capacity when power is transmitted from bus v to bus w [27], which is calculated as

$$C_{vw} = \min_{l \in L} \left\{ \frac{P_l^{\max}}{\left| Pf_l^{vw} \right|} \right\}, \tag{6}$$

where Pf_l^{vw} is the power transfer distribution factor (PTDF) of line l when one unit of power injected at bus v and withdrawn from bus w; $P_l^{\max}$ is the power flow limit about transmission line l.

To improve the flexibility of ECS, we may further upgrade the ECS by changing the proportions of C_{vw} and Z^E_{vw}. In (2), ω and ξ are proportions coefficients whose sum is equal to 1. In this paper, a community detected only by an ECS distribution [25] is denominated an **electrical community** which is **only consistent with meaning 1** above-mentioned (only coupling strength is considered).

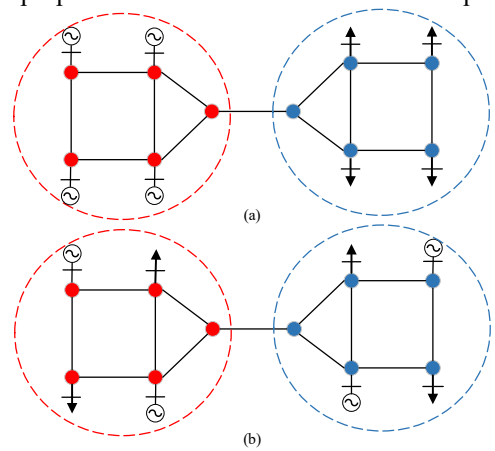


Fig. 1. The impact of node type distribution on power grids partitioning.

Node type distribution is central for power network partitioning [23]. Fig. 1 is an example to explain the effect of node type distribution on the power network partitioning regarding meaning 2. The topological structure and parameters of lines are identical in (a) and (b). If only ECS, representing coupling strength in meaning 1, is utilized for partitioning as in [25], the networks of (a) and (b) can be partitioned into two electrical communities in the same way. However, in case (a), all generation buses are in the left community, and all load buses are placed in the right community. Such a partitioning result cannot satisfy the self-balancing and independence of power supply within a partitioned sub-network and cannot accord with meaning 2 in Section A. No power can be supplied within the same community, but all be transmitted from the left to the right community. Therefore, such community structures are not meaningful from the perspective of power supply functionality. In comparison, each community in case (b) contains two generation buses and two load buses. So, more power supply could be performed between source and sink nodes within the same community and less inter-community transmission could be detected. Therefore, case (b) in Fig. 1 is more consistent with two meanings of functional community.

Considering the functionality of power supply and the association between generation and load in the network, PSS is originally proposed to reflect the influence of a given source-sink relation and to quantify the association among generation buses and load buses [28]. The PSS between generation bus g and load bus d is defined as

$$\overline{S}_{gd} = \left| d\overline{Y}^d_g + jl\,\overline{T}^d_g \right|, \tag{7}$$

$$\overline{Y_g^d} = \frac{Y_g^d}{\overline{Y}} = \frac{\frac{1}{Z_g^d}}{\overline{Y}}, \tag{8}$$

$$\overline{\mathrm{T}_g^d} = \frac{\mathrm{T}_g^d}{\overline{\mathrm{T}}}, \tag{9}$$

where Y_g^d is the equivalent admittance between generation bus g and load bus d; T_g^d is the valid capacity for power transmission from generation bus g to load bus d.

As in (2), we normalized two quantities in (7), and the two coefficients δ and λ are used to change the proportions of equivalent admittance and capacity. $\overline{Y}$ and $\overline{T}$ are the average values of equivalent admittance and valid capacity.

In (8), Z_g^d is the electrical distance from bus g to bus d, defined as

$$Z_g^d = z_{gg} - 2z_{gd} + z_{dd}. \tag{10}$$

In (9), the magnitude of T_g^d is equal to the minimum value of the capacity at generation bus, load bus and the equivalent transmission capacity of the network between g and d as

$$\mathrm{T}_g^d = \min\{\tau_g, \tau_{gd}, \tau_d\}, \tag{11}$$

where τ_g is the capacity of generation on bus g; τ_d is the capacity of load on bus d; τ_{gd} is the power transmission capacity depending on network connection, which is similar to (6).

$$\tau_{gd} = \min_{l \in L}\left\{\frac{P_l^{\max}}{|Pf_l^{gd}|}\right\}, \tag{12}$$

where Pf_l^{gd} is the PTDF of line l when one unit of power is injected at generation bus g and withdrawn from load bus d; P_l^{max} is the power flow limit about line l between g and d.

A key difference between ECS and PSS is that only the value of PSS between a generation bus and a load bus is non-zero, all other values of PSS are zero. But the values of ECS between any two buses are non-zero. The PSS can make grouping for generation and load buses, but insensitive for transmission buses.

C. Electrical functional strength matrix

As discussed in Section A, a power supply community should consider the two proposed meanings of functional community structures. The functionality of buses in power grids reflect these two aspects: a) buses construct paths for power transmission evaluated by ECS for meaning 1; b) buses perform as a source or sink in the power supply evaluated by PSS as for meaning 2. In addition to the generator buses and the load buses, the distribution of transmission buses also affects the connectivity of each node in the power network partition. Different from our previous preliminary works [25][28], to describe power supply communities by integrating the two meanings previously discussed, we propose the concept of EFS, which combines ECS and PSS.

As discussed in the previous section, ECS is proposed to reflect characteristics of buses and lines about power transmission efficiency. Based on the (2), the **ECS matrix** is defined as following

$$\boldsymbol{E}_{vw} = \overline{E}_{vw}, \quad \text{Between any bus } v \text{ and bus } w. \tag{13}$$

Moreover, PSS describes the power supply (source-sink) relation and features between generation buses and load buses based on the structural and functional characterization of power networks. The **PSS matrix** can be characterized by (7) as

$$\boldsymbol{S}_{ij} = \begin{cases} S_{gd} = S_{dg} = \overline{S}_{gd}, & \text{Between generation bus } g \text{ to load bus } d \\ 0, & \text{otherwise} \end{cases} \tag{14}$$

Compared with the conventional adjacency matrix in which the elements are non-zero only between nodes that have a direct connection, all off-diagonal elements in the ECS matrix are

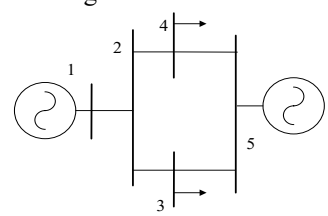


Fig. 2. Network example.

non-zero, but only the corresponding elements between generation buses and load buses are non-zero in the PSS matrix. Considering the two meanings of a functional community structure, the EFS matrix is established by combining the ECS matrix and the PSS matrix.

The element corresponding to bus i and bus j in ***EFS*** matrix is expressed as

$$\boldsymbol{EFS}_{ij} = \boldsymbol{E}_{ij} + \boldsymbol{S}_{ij}. \tag{15}$$

The ***EFS*** reveals the functional characteristics between power grid buses for power transmission and power supply relations. A community detected by ***EFS*** is named as a **power supply community**. In Section III, it will be shown that buses with higher EFS may have more probabilities to be partitioned in the same community. Equation (15) is to intensify the strength between a generation bus and a load bus, so the partitioning algorithm could integrate and take account of both meaning 1 and meaning 2.

D. Adjacency matrix versus *EFS*

In this section, to compare ***EFS*** with a conventional adjacency matrix, we use the network example illustrated in Fig. 2 which specific data in is provided in Appendix A. The adjacency matrix of the network shown in Fig. 2 is

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

Depending on (15), the ***EFS*** of Fig. 2 is

$$\boldsymbol{EFS}_{ij} = \boldsymbol{E}_{ij} + \boldsymbol{S}_{ij}$$

$$= \begin{bmatrix} 0 & 0.44 & 0.42 & 0.42 & 0.41 \\ 0.44 & 0 & 0.83 & 0.92 & 0.91 \\ 0.42 & 0.83 & 0 & 0.86 & 1.30 \\ 0.42 & 0.92 & 0.86 & 0 & 0.83 \\ 0.41 & 0.91 & 1.30 & 0.83 & 0 \end{bmatrix} + \begin{bmatrix} 0 & 0 & 0.42 & 0.42 & 0 \\ 0 & 0 & 0 & 0 & 0 \\ 0.42 & 0 & 0 & 0 & 1.30 \\ 0.42 & 0 & 0 & 0 & 0.83 \\ 0 & 0 & 1.30 & 0.83 & 0 \end{bmatrix}$$

$$= \begin{bmatrix} 0 & 0.44 & 0.84 & 0.84 & 0.41 \\ 0.44 & 0 & 0.83 & 0.92 & 0.91 \\ 0.84 & 0.83 & 0 & 0.86 & 2.60 \\ 0.84 & 0.92 & 0.86 & 0 & 1.66 \\ 0.41 & 0.91 & 2.60 & 1.66 & 0 \end{bmatrix}$$

The adjacency matrix only has a non-trivial value when the

two buses are connected directly, but it cannot reflect the interactions between every bus (direct or non-direct connection). However, for power networks, the energy can still be transferred between buses that are not directly connected. For example, in the adjacency matrix, the weight is 0 between the generation bus 1 and load bus 3, but the element is 0.84 in ***EFS***. Moreover, the component of the adjacency matrix is 1 or 0, so it cannot reflect the differences and the capability of transmission between buses in the network. The magnitude of EFS of branch 2-3 and branch 2-4 is 0.83 and 0.92, but in the adjacency matrix, the values of A_{23} and A_{24} both are 1. Relative to the adjacency matrix, the ***EFS*** matrix reveals the relations among nodes from a different perspective, better reflecting the interaction between all nodes and the influence of different types of node distribution in power networks during energy transmission.

III. Partitioning Algorithm for Power Supply Communities

A. Power supply modularity

In the process of investigating the community structure of networks, modularity is a widely applied metric to quantitatively evaluate the partitioning results in complex networks [11]. The definition of modularity Q refers to the difference between the proportion of edges connected to the internal nodes of a community and the expected value of that proportion in a random network [15]-[17]. If the topological community structure is well-partitioned, the density of the internal connections is higher than the expected level of the randomly connected network [17]. The higher the value of Q, the better the partition results, and the modularity is defined as (16).

$$Q = \frac{1}{2m}\sum_{ij}\left(A_{ij} - \frac{k_i k_j}{2m}\right) d(c_i, c_j), \tag{16}$$

where A_{ij} denotes an element in the adjacency matrix, m is equal to½ $\sum_{ij} A_{ij}$ which represents the number of edges in the network, $k_i(k_j)$ is the degree of vertex $i(j)$ and $c_i(c_j)$ is the community that vertex $i(j)$ belongs to. The δ-function is 1 if nodes i and j are in the same community, otherwise, it is 0.

The modularity Q evaluates the performance of community detection based on the adjacency matrix. As discussed in the previous section, the adjacency matrix can only reflect the pure topology of the network, but it cannot reflect the functionality and special electrical characteristics of power grids.

To consider the complex electrical properties and the functionality of power networks, this paper proposes the concept of **power supply modularity (Q_{PS})**, which integrates electrical functional strength and modularity as a benchmark for evaluating power network partitioning results.

For this, the total EFS of the whole power grid system is defined as

$$F = \frac{1}{2}\sum_{ij} EFS_{ij}. \tag{17}$$

Subsequently, the EFS degree of bus i is

$$EFS_i = \sum_{j} EFS_{ij}. \tag{18}$$

Then, the Q_{PS} can be defined as

$$Q_{PS} = \sum_{ij}\left(\frac{EFS_{ij}}{2F} - \frac{EFS_i}{2F}\frac{EFS_j}{2F}\right) d(c_i, c_j). \tag{19}$$

In a given power network **G,** if one unit of EFS is taken randomly, the probability of this unit of EFS connecting from bus i to bus j should depend on following two events:

- Event I: this unit of EFS is connected to bus i;
- Event II: this unit of EFS is connected to bus j.

Initially, the probability of event I is EFS_i/2F. Since the value of the EFS between bus i and bus j is already known for **G**, Event I and II are not independent. Therefore, the probability of event II is EFS_{ij}/EFS_i. Consequently, the probability of this unit of EFS between bus i and bus j is calculated as $(EFS_i/2F)\cdot(EFS_{ij}/EFS_i)$=$EFS_{ij}$/2F.

TABLE II
COMPARISON ABOUT ECS AND EPS IN FIG. 1

	Q_{PS}	The modularity based on ECS
Case (a)	0.0277	0.1275
Case (b)	0.1493	0.1275

Subsequently, a network **R** is proposed as a benchmark that has the same number of buses and the total value of EFS as network **G**. The EFS degree for any node in network **R** is equal to the EFS degree in network **G**. The difference between network **R** and network **G** is that the distribution of EFS is random in the network **R**; hence, events I and II are independent. Similarly, when one unit of EFS is randomly picked from **R**, the probability corresponding to event I is still equivalent to EFS_i/2F, while the probability of event II is EFS_j/2F because events I and II are independent. Thus, the probability of this unit of EFS connecting bus i and bus j is $(EFS_i/2F)\cdot(EFS_j/2F)$. Equation (19) just represents the probability difference between **G** and **R**. A better partitioning of network **G** should have larger power supply modularity representing higher probabilities of internal EFS distribution inside a community compared with a random network **R**.

As discussed in Fig. 1, the ECS only considers coupling strength in meaning 1, which ignores the node type distribution in network partitioning. To further demonstrate this point, the networks of (a) and (b) in Fig. 1 are utilized to make a comparison. If the ECS is applied as a weight to partition the network, the modularity should be calculated as [25]

$$Q_{ECS} = \sum_{ij}\left(\frac{ECS_{ij}}{2M} - \frac{ECS_i}{2M}\frac{ECS_j}{2M}\right) d(c_i, c_j),$$
$$M = \frac{1}{2}\sum_{ij} ECS_{ij}, \quad ECS_i = \sum_{j} ECS_{ij}. \tag{20}$$

Then, we compute the Q_{PS} and the modularity based on ECS of cases (a) and (b). The results are shown in Table II. For cases (a) and (b), the magnitudes of modularity based on ECS are the same. But the Q_{PS} of case (a) decreased much compared with the modularity based on ECS. On the contrary, the Q_{PS} of case (b) increased and is much higher than case (a). Because of more transboundary power interaction, community characteristic is much weak in case (a). But with more local power interaction within the same region community characteristic is more obvious in case (b). Case (b) in Fig. 1 is more consistent with

two meanings of functional community. Q_{PS} can give perfect evaluation for these features.

B. Modified partitioning algorithm for power supply networks

The Newman fast algorithm is a widely accepted community detection method [15] that is based on the idea of modularity. Considering the electrical characteristics and functionality of power networks, the Newman method is redesigned by replacing conventional modularity with Q_{PS}. The modified Newman partitioning algorithm is outlined in Algorithm 1. The detail process is provided in Appendix B.

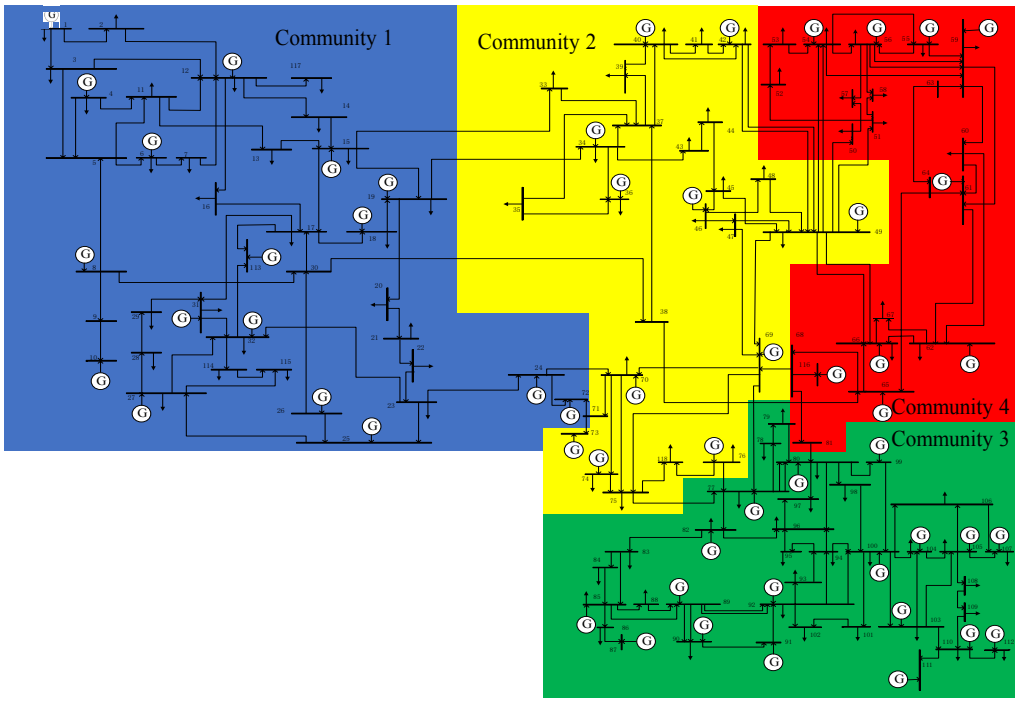


Fig. 4. One-line diagram of the IEEE 118-bus system with four communities partitioned by proposed partitioning method.

IV. CASE STUDY

In this section, to analyze and verify the performance of the proposed partitioning method, we study the IEEE-118, IEEE-300 bus systems and an Italian power grid as test cases. Moreover, we compared the partitioning results of the proposed method with other published methods. All the computations were performed in MATLAB. The experimental operating environment is a Microsoft Windows 7 (64-bit) operating system with a core i5-6500 CPU 3.20 GHz and 8GB RAM.

TABLE III
THE DESCRIPTION OF PARTITIONING RESULTS FOR DIFFERENT SYSTEMS

	Community No.	Q	Q_{PS}	Number of buses	Number of branches
IEEE-118 bus system	1	0.7052	0.08477	37	50
	2			25	33
	3			35	52
	4			21	29
IEEE-300 bus system	1	0.8285	0.08708	85	113
	2			118	151
	3			97	130
Italian power network	1	0.8334	0.1214	73	84
	2			34	33
	3			62	71
	4			61	69
	5			55	59
	6			76	86
	7			50	56
	8			87	97
	9			23	22

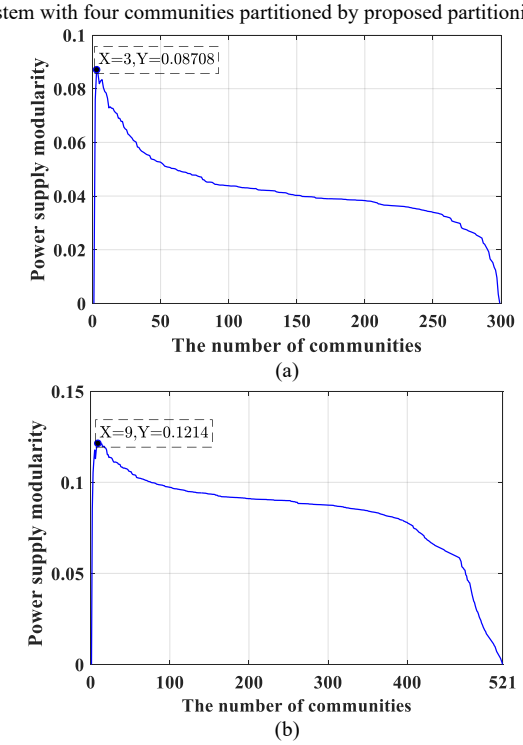
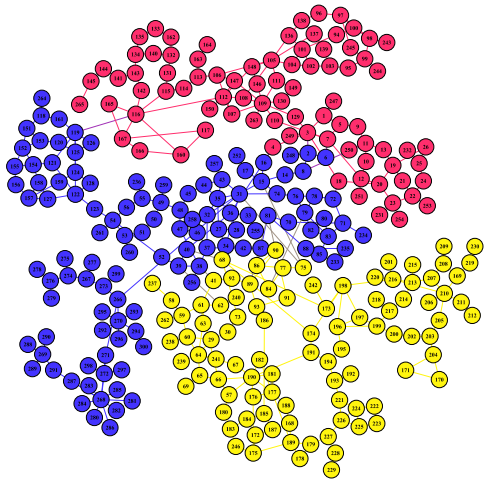


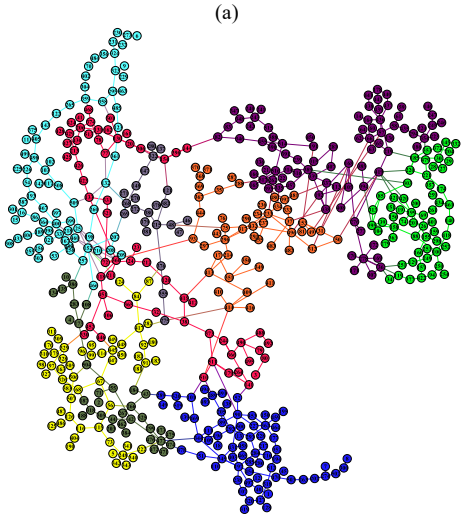
Fig. 5. Value of power supply modularity with the number of communities in (a) IEEE-300 bus system (b) Italian power network.

A. Experimental results of different systems

The partitioning method proposed in this paper is applied to the IEEE-118 bus system. The proportion coefficients (ω, ξ, δ and λ) are equal to 0.5 in (2) and (7). Fig. 3 shows the relationship between the number of communities and power supply modularity.



(a)



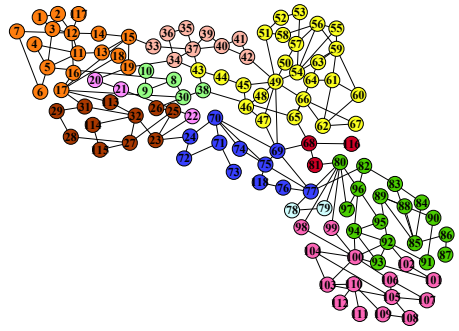
(b)

Fig. 6. Graph with the nodes of partitioning results in (a) IEEE-300 bus system (b) Italian power network.

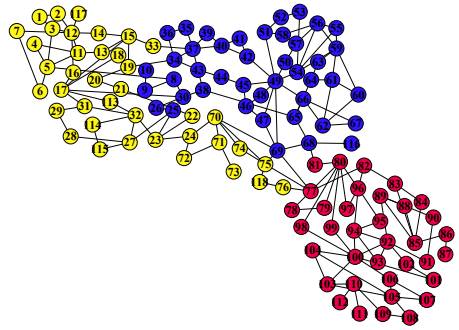
In Fig. 3, the Q_{PS} reaches the maximum value (0.08477) when the network is partitioned into 4 communities. Fig. 4 displays the one-line diagram of the IEEE-118 bus system with these four communities. In Fig. 4, the different colors are utilized to represent diverse communities. Additionally, to further analyze the performance of the proposed partitioning method in large-scale power networks, Fig. 5 shows the relationship between the number of communities and power supply modularity of the IEEE-300 bus system and an Italian power network. The IEEE-300 bus system is grouped into 3 communities when the maximum Q_{PS} is equal to 0.08708. Moreover, the partitioning result of the Italian power network is 9 communities, with a maximum Q_{PS} of 0.1214. Table III describes the specific partitioning results of the different systems. Fig. 6 shows the macro graph of partitioning results by the proposed method in the IEEE-300 bus system and the Italian power network.

B. Power flow analysis

In this section, we obtain and compare three partitioning results by three different modularity calculated with three matrixes (EFS, ECS and adjacency matrix). The IEEE-118 bus system is considered as a reference to enact the comparison. Fig. 7 presents the three partitioning results in the IEEE-118 bus system.



(a)



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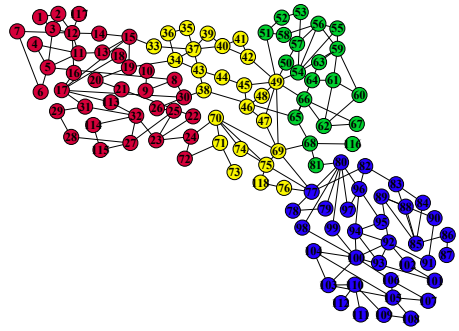

(c)

Fig. 7. Partitioning results obtained by (a) adjacency matrix (b) electrical coupling strength (c) electrical functional matrix in the IEEE-118 bus system.

Fig. 7(a) shows the partitioning results (11 communities) in the IEEE-118 bus system by the conventional Newman fast algorithm (which is based on the adjacency matrix), while Fig. 7(b) displays the partitioning results (3 communities) based on the ECS [25], which corresponds to meaning 1 mentioned in section II. Fig. 7(c) is the macro graph of partitioning results by the method based on the EFS matrix (proposed in Section III) which reflects both meaning 1 and 2.

Corresponding to meaning 1, to evaluate the capability and efficiency transmitting physical elements between buses within a community, we proposed the power loss factor (PLF) which is the proportion of the power losses to the total power flow in the same community. PLF can be calculated as

$$PLF = \frac{\hat{\mathrm{A}}_{vw}\left|Ploss_{vw}\right|}{\hat{\mathrm{A}}_{vw}\left|P_{vw}\right|}, \tag{21}$$

where bus v and bus w are in the same community; $Ploss_{vw}$ and P_{vw} are power loss and power flow respectively between bus v and bus w. The smaller the PLF value, the higher efficiency to transfer physical elements between nodes within the community, compared to transmission to external nodes.

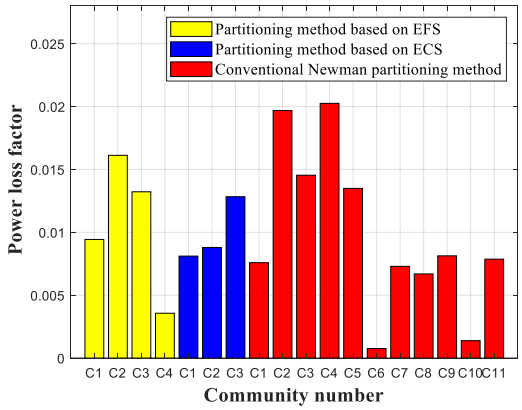

Fig. 8. The average PLF of different partitioning results.

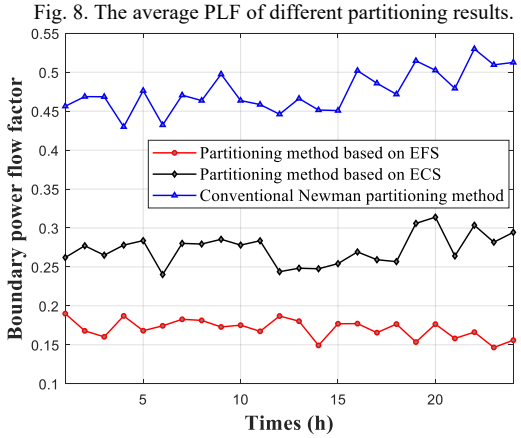

Fig. 9. The BPFF per hour for three partitioning results.

Additionally, according to meaning 2 for functional community structure, a reasonable power network partitioning should have a lower boundary power flow relative to the whole network load. Boundary power flow is an important evaluating factor for partitioning power grids into different managing areas [29]. To represent this property, the concept of the boundary power flow factor (BPFF) is proposed, defined as

$$BPFF = \frac{\hat{A}_{ij}\left|P_{ij}\right|}{\hat{A}_{w}P_{Lw}}, \tag{22}$$

where, P_{ij} is the boundary power flow among bus i and bus j (i and j belong to different communities); P_{Lw} is the capacity of load on bus w. Lower BPFF values represent stronger intra-zone power supply and weaker external interaction.

For studying the uncertainty of power system caused by the fluctuation of loads and the change of operation modes, we modeled different operating conditions and the change of loads in the IEEE-118 bus system in 24 hours using Monte Carlo simulation (MCS). Then, using MATPOWER [30], we performed the optimal power flow calculation to each hour of sampling loads and obtained the results of the probabilistic load flow. The random model of loads inside the system is characterized as the Gaussian distribution [31], [32]

$$f_l(i) \sim N(m, s^2), \tag{23}$$

where f_l is the probability density function of load levelling within target periods; the value of μ and σ are based on the IEEE-RTS [33] that provides hourly and seasonal peak load.

For completing the analysis, we calculated the average PLF of each community for the period of 24 hours for the different partitioning results shown in Fig. 7 based on the results of the probabilistic load flow in each hour. The PLF results are shown in Fig. 8. The conventional Newman partitioning algorithm divides the IEEE-118 bus system into 11 communities (note that the scale two or three buses within the communities are too small). PLF values are quite uneven and are not able to capture meaning 1. So, this partitioning result is meaningless from the perspective of engineering. PLF values based on EFS and ECS are close, which demonstrates that the partitioning results obtained by these two methods have similar performance with respect to meaning 1. Furthermore, in case of an outage in community i, the response of communities could be analyzed from two aspects: (1). For other communities other than i, to avoid impacts from the outage, the other communities could make islanding operation. If the partitioning is reasonable, each community could have best self-sufficiency in power supply capability, most loads can still have power supply. In Fig. 7(a), the sizes of communities are quite heterogeneous. Some communities have poor balance in power supply and demand. Partitioning by our method may obviously have better performance from this point of view; (2). For community i, in islanding operation, the final performance depends on protection devices and the self-control capability within the community. A reasonable partitioning with better supply-sufficient capability should have better performance in responding to outage. Therefore, in summary, the capabilities of communities in dealing with outages mainly depend on supply-sufficient capability in each area, but not numbers of communities. And this is just the advantage of our method.

TABLE IV
PARAMETERS OF LOADS AND THE VALUE OF AVERAGE BPFF OF EIGHT SCENARIOS

Season	Scenario	μ	σ	**EFS**	ECS	Conventional
Spring	Weekday	0.6510	0.0103	**0.1541**	0.2358	0.4446
	Weekend	0.5119	0.0058	**0.1546**	0.2366	0.4460
Summer	Weekday	0.6176	0.0099	**0.1529**	0.2320	0.4419
	Weekend	0.4952	0.006	**0.1513**	0.2261	0.4458
Fall	Weekday	0.6835	0.0141	**0.1550**	0.2399	0.4477
	Weekend	0.5290	0.0081	**0.1509**	0.2281	0.4457
Winter	Weekday	0.6610	0.0111	**0.1541**	0.2368	0.4450
	Weekend	0.5324	0.0072	**0.1505**	0.2278	0.4446

Furthermore, we calculated the BPFF per hour of three partitioning results, as illustrated in Fig. 9. The BPFF per hour of the method based on an EFS is lower than the conventional Newman partitioning method and that based on the ECS. This result is consistent with the meaning 2 of functional community mentioned in Section II, that is, there are more physical element interactions inside communities than between communities. Furthermore, this result proves that with reasonable partitioning, OPF may only focus on economic aspect, requirement of self-sufficiency can be met naturally. But if partitioning is not reasonable (such as the other two methods), OPF has to take boundary power flow into objective function, which may make sacrifice in economy. To further verify the benefits of EFS in complex characteristics of power consumption, we consider that the load curves on weekdays and weekends are different. Eight scenarios are modelled based on the IEEE-RTS [33]. Table IV lists the parameters set and the value of average BPFF of eight scenarios corresponding to three partitioning results. Similarly, the BPFF of the method based on an EFS is lower than the conventional Newman partitioning

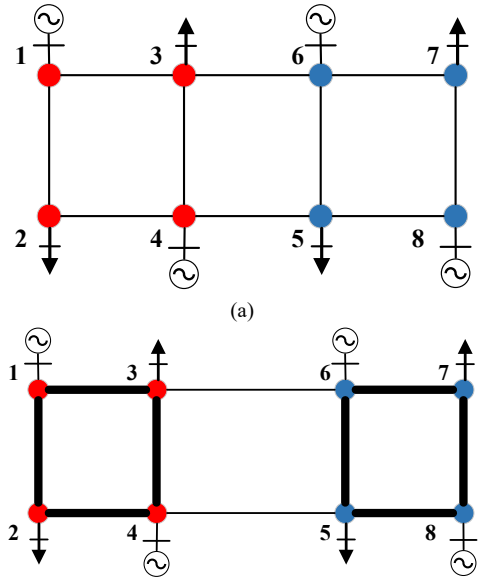

Fig. 10. Two cases with same topological structure but different physical features.

TABLE V
PARAMETERS FOR CASES IN FIG. 10

Branch	Case (a)	Case (b)
3-6, 4-5	P^{max}=1; Z=1	P^{max} =1; Z=100
1-2, 1-3, 2-4, 3-4, 5-6, 5-8, 6-7, 7-8	P^{max} =1; Z=1	P^{max} =100; Z=1

TABLE VI
COMPARISON BETWEEN TWO CASES IN FIG. 10

	Bus pair	ECS	Q	Q_{PS}
Case (a)	(1,2)	0.7827	0.3	0.0126
	(1,8)	0.5617		
Case (b)	(1,2)	1.5768	0.3	0.4753
	(1,8)	0.0339		

method and that based on the ECS in Table IV. In different operating scenarios, the boundary power flow of our method is always the minimum, which means the partitioned areas can operate more independently and have better supply-sufficient capability. Considering these, the above analysis strongly suggests that the approach based on EFS proposed in Section III can better identify power supply communities in power grid applications.

C. Comparison against conventional modularity

It should be emphasized that the values of Q_{PS} (mostly smaller than 0.1) in Table III are all much smaller than conventional modularity Q (around 0.7 or 0.8). Detailed explanation can be given by cases (a) and (b) in Fig. 10. Power flow limit and impedance of each line for these two cases are given in Table V. Comparison of results are shown in Table VI.

In case (a), with the same power flow limit and impedance for all lines, Q_{PS} is much smaller than the conventional Q. We can consider two bus pairs (1,2) and (1,8). From topological perspective, bus 1 and 2 are nearest and bus 1 and 8 are furthest. However, ECS values of these two pairs in case (a) are not quite different. The main reason is that all paths in the whole network between two buses may contribute to their power transmission, so the ECS distribution in the whole network may be much even. Therefore, the community characteristic evaluated by Q_{PS} is not quite remarkable. But in case (b), when the impedance of boundary lines has been enlarged much and the power flow limit of internal lines has been enlarged much, Q_{PS} has increased to 0.4753 which is even much higher than the conventional Q. This can justify that Q_{PS} can successfully catch and evaluate strong community characteristics from functional and engineering perspective, but the conventional modularity failed to do this. In many previous works, conventional modularity Q has been utilized as a criterion to assess the partitioning results of power grids [18]-[20]. However, as indicated by Table III, **we argue that the conventional Q may exaggerate community characteristics of power grids**. But the proposed Q_{PS} could be a better criterion for assessing partitioning of power grids.

TABLE VII
PERFORMANCE COMPARISONS BETWEEN THE PROPOSED METHOD AND OTHER PREVIOUS METHODS IN IEEE-118 BUS SYSTEM

Method	Number of communities	Q_{PS}
Partitioning method in Section III	4	0.0848
partitioning method based on local similarity [15]	8	0.0692
Generational Genetic Algorithm (GGA+) [16]	8	0.0668
Conventional Newman fast algorithm	11	0.0671

D. Comparison against previous published methods

In this section, we compared the algorithm proposed in Section III against previously published methods to further assess its performance. The partitioning results of the IEEE-118 bus system obtained by different methods are compared in terms of Q_{PS}. Table VII lists the power supply modularity of different partitioning methods. The IEEE-118 bus system is partitioned into 8 communities by the partitioning methods in [18] and [19], which have Q_{PS} values of 0.0692 and 0.0668, respectively. The modified Newman partitioning method proposed in Section III divides the IEEE-118 bus system into 4 communities with a Q_{PS} of 0.0848. Therefore, the proposed power supply modularity performs better in detecting functional and electrical characteristics.

For further investigations, we compared the conventional Newman fast algorithm with the proposed partitioning method. In Table VII, the optimal partitioning result by the original Newman fast algorithm is 11 communities with a Q_{PS} (0.0671) that is lower than the one computed by the proposed partitioning method. The comparison of results proves that the modified Newman partitioning method proposed in this paper is more reasonably found using an engineering viewpoint and accurately partitions power grids compared with the approaches proposed in previous studies.

V. CONCLUSIONS

Community detection is an important research direction in the field of investigating the topology of complex networks. In most power systems, the functional characteristics of networks cannot be ignored. Hence in power systems, for different network partitioning issues, both the specific structural and functional characteristics of the network should be considered. In this work, we propose the functional community as a mean to describe the structural and functional characteristics of power

networks. By considering two meanings of functional communities, we defined the electrical functional strength combined with the structural and functional characteristics of power grids. By applying this approach to representative cases, we have verified that the EFS can work as a weight to reflect the two specific meanings in power supply communities. Then, the concept of modularity is redefined as power supply modularity to evaluate the power grid partitioning performance. Furthermore, the conventional Newman fast algorithm was modified based on power supply modularity. Taking the IEEE-118, IEEE-300 bus systems, and an Italian power grid as test cases, we have proved that the proposed partitioning method performs well when compared to other methods. We also found that **conventional modularity may exaggerate community characteristics of power grids** and not appropriate as a criterion for power grids. Or **the topological communities may not take accordant performance in functionality**. It is highly possible that **this phenomenon may also exist in other engineering networks**.

These results demonstrate that the structural and functional characteristics of networks are of great consequence when analyzing the construction of a complex network. The concept of functional community can provide an innovative perspective. Different networks include disparate structural and functional characteristics. Therefore, specific engineering characteristics should be considered when partitioning different engineering networks. In the future, the proposed method will be adapted to other complex networks such as transportation networks.

APPENDIX A

The network example is illustrated in Fig. 2. The system data is provided in Table A.I and A.II. The data is on 100 MVA base.

TABLE A.I
BRANCH DATA

Branch	Resistance (p.u)	Reactance (p.u)	Susceptance (p.u)	Power Flow Limit (p.u)
1-2	0.0035	0.0411	0.6987	99
2-3	0.0010	0.0250	0.7500	99
2-4	0.0013	0.0151	0.2572	99
3-5	0.0070	0.0086	0.1460	99
4-5	0.0013	0.0213	0.2214	99

TABLE A.II
LOAD AND GENERATOR DATA

Bus Number	Load		Bus Number	Generation	
	P_d (MW)	Q_d (MVAr)		P_g (MW)	Q_g (MVAr)
3	322	2.4	1	250	162
4	500	184	5	678	222

APPENDIX B

Algorithm 1: Modified Newman fast algorithm for power supply network partitioning	
	Input: network data, EFS matrix
	Output: partitioned result
1 :	Initialize power network with N communities;
2 :	Calculate the Q_{PS};
3 :	**while** the number of communities is not 1 **do**
4 :	**if** there is direct connection between two communities **then**
5 :	Group two communities randomly;
6 :	**else**
7 :	The communities cannot be grouped together;
8 :	**end if**
9 :	Calculate the increments of electrical functional modularity ΔQ_{PS};
10 :	Select the partitioning with maximum ΔQ_{PS};
11 :	Recalculate Q_{PS} according to the result of partitioning;
12 :	Conserve the number of communities (The maximum number of mergers is N-1);
13 :	**end while**

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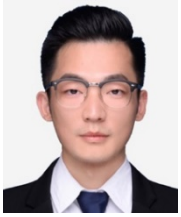

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