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How to Couple Two Networks for a Smart Grid

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ABSTRACT Smart grids, which are composed of reciprocal power grids and communication networks, have revolutionized the traditional electrical section. Interdependent smart grids have attracted many researchers to the cascade scheme. However, the strategy of coupling two networks has been neglected. The construction of a real coupled network has been infeasible due to the economic cost and network scale for researchers. Therefore, coupling two networks to simulate a real network is fundamental for a smart grid. In this paper, we propose a model for the coupled network, analyze the characteristic of power network, and focus on the coupling strategy. Next, we leverage a classic community detection algorithm to form a local network. A new local positive degree coupling algorithm was proposed based on community detection to create a coupled network. A numerical experiment demonstrates that our coupling algorithm outperforms the previous random coupling scheme. In addition, the local positive degree coupling algorithm can be extended to other cyber-physical systems with slight changes for future studies.

INDEX TERMS Community detection, large scale network, random coupling scheme, smart grid, simulation network.

I. INTRODUCTION

Smart grids, which have incited a revolution in traditional electrical grids, integrate various smart infrastructures and renewable energy sources. A smart grid, coupled with widespread power networks and intelligent communication networks, has formed a reciprocal network. Power stations depend on communication networks for control and management, whereas communication networks depend on power systems for their electricity support. A smart grid has a salient feature: the coupling of two interdependent networks rather than the use of a single isolated network. This feature has attracted many researchers to the cascade scheme due to essential power security. Some results are remarkable [1], [2].

Electrical energy is instantaneous and cannot be stored in its original form on a large scale; as a result, a experiment that considers an economic and large-scale network for researchers is infeasible [3]. Therefore, simulation is fundamental for a smart grid [4].

Many researchers have concentrated on cascade control and alleviation in interdependent networks [2], [5]. Most of those studies were based on completely random coupling, which is a strong condition for a coupled network [6]. Many real-world networks (e.g., smart grid) are not randomly deployed but are carefully designed to achieve performance and function [1]. Thus, a random coupling strategy is not suitable for a real network with regard to both theory and experiment. However, connection with every determined node point-by-point remains unrealistic for large-scale networks. A power grid has a distinguished modulation property [7]. Therefore, coupling two heterogeneous networks for a smart grid becomes a challenge considering the modularity of a power network.

Few studies address coupling strategies. Shin, et al. investigated unidirectional and bidirectional inter-edges to affect the cascade [1]. Four types of relationships (power flow, power supply, communication signal and control data) were investigated in [8]. An allocation of the edges between a power grid and a communication network was proposed [9]. The allocation followed a well-known balls and bins model of probability and provided the interlinks between a power grid and the Internet. How the edges connected two networks remains unclear in these studies.

The coupling method, which is a one-to-one connection, can be traced in [10] regarding the vulnerability of the coupled network. Wang *et al.* [11] considered a one-to-two connection method to ensure the connection of two communication nodes with a power node. However, these studies did not provide clear descriptions.

Considering the modulation property, some studies of a separating network in a smart grid system were proposed. To consider the geographical correlated failures [12], the authors divided an Italian transmission network into mangy disk centers. In [13], a regional division in a smart grid was envisioned. These studies did not clearly address the problem of coupling two networks for a smart grid.

The community detection algorithm can connect related nodes to establish a community, in which nodes are easily connected. The majority of power applications are restricted to many factors, such as time delay, management and geographical area [14]. Thus, nodes prefer to communicate in an inner community rather than an inter community. Intuition enlightens us to the use of the community detection algorithm to build a coupled network.

Based on intuition, we propose a coupling scheme and weaken the condition of complete randomness, considering the modulation of the power grid. First, we construct a model to represent a coupled network and propose a specific problem. Second, we provide a coupling algorithm to couple two networks based on the classic community detection algorithm. An algorithm analysis is also presented. In the experiment, we simulate the coupling scheme and compare the results of algorithms. The main contributions are summarized as follows:

- The model for an interdependent network is given. Based on this model, we formulate a specific problem.
- In the coupling scheme, we weaken the condition of complete randomness and propose a community algorithm based on community detection.
- We present a positive degree coupling algorithm and perform an algorithm analysis.
- With open NetworkX, we set up an experiment and compare the performance of algorithms.

In the remainder of this paper, we construct a model for the interdependent network in section II. Section III introduces and analyzes the coupling algorithm. An experimental evaluation and a discussion of the results are provided in section IV. The study's conclusions are presented in section V.

II. NETWORK MODEL

In this section, we introduce the model for the coupled network and propose useful definitions for the coupled network. The research problem is based on this model. Basic notations are summarized in Table 1.

A. NETWORK MODEL

The electrical energy has a hierarchical level and supply for consumption equipment. A node in a power network has many properties, such as load, power level, geographical position, and administrator node. The administrator node, which manages the neighbor nodes when a fault has occured, is specific for each power node due to the rigorous requirement of security. We use the n-dimensional vector x^p to represent a power node. Different dimensions represent different properties. The power node set $P = (x_1^p, x_2^p, \ldots, x_s^p)$ implies that the power grid include s nodes. An adjacent matrix A^p represents the mutual connection among the power nodes. Similarly, a node of communication network can be modeled as the m-dimensional vector y^c. Each communication node has multi-properties, such as administrator node and type. The communication node set $C = (y_1^c, y_2^c, \ldots, y_t^c)$ signifies that the communication network includes t nodes. The adjacent matrix A^c can represent the relationship among communication nodes. The coupled matrix $R_{s\times t}$ represents the coupling information between power nodes and communication nodes, since each power node has at least one coupled communication node. Therefore, the coupled network G can be presented as five-tuple model:

TABLE 1. Basic notations.

Symbol	Definition and Description
A	adjacency matrice
x,y	column vector
$a_{i,j}$	element at row i column j in adjacent matrix A
d_i	node degree of i
c_i	community to which node i belongs
$\omega(x)$	weight vector of x
$\|\|.\|\|$	norm of vector

$$G = (P, A^p, C, A^c, R) \tag{1}$$

Definition (Inner-Network Distance): Assume that x_i^p and x_j^p are two power nodes; the inner-network distance is $dis_{x_i,x_j}^p = \left\| x_i^p - x_j^p \right\|$. Likewise, if y_i^c and y_j^c are two communication nodes, the distance denotes $dis_{y_i,y_j}^c(y_i^c, y_j^c) = \left\| y_i^c - y_j^c \right\|$.

Definition (Administrator Node): The administrator node $Ad_j = \{(Ad_j \in P) \vee (Ad_j \in C)\}$, and node $\{j | d_j \in \max_k \{d_1, d_2, \cdots, d_n\}, 1 \leq k \leq n\}$. Because this node is usually located in a town or a city, an administrator node, which is always referred to as a power supply bureau, can manage many nodes in a power network and communication network.

Definition (Inter-Network Distance): Assuming that x_i^p and y_j^c are the power node and communication node, respectively. An internetwork distance can be defined as $dis_{x_i,y_j}(pu, pv) = \left\| x_i^T \cdot pu - y_j^T \cdot pv \right\|$. The parameters pu and pv satisfy $\sum_i pu_i = 1$ and $\sum_j pv_j = 1$. For example, $pu = (0, 0, 1, 0, 0, \ldots)$ indicates that we take the third component of vector x_i for the calculation.

Figure 1 shows an intuitive model of the coupled network. The red bold solid line represents a power line, whereas the black solid line is an inner link of nodes located in the communication network. The black dashed line represents the interlink of two networks.

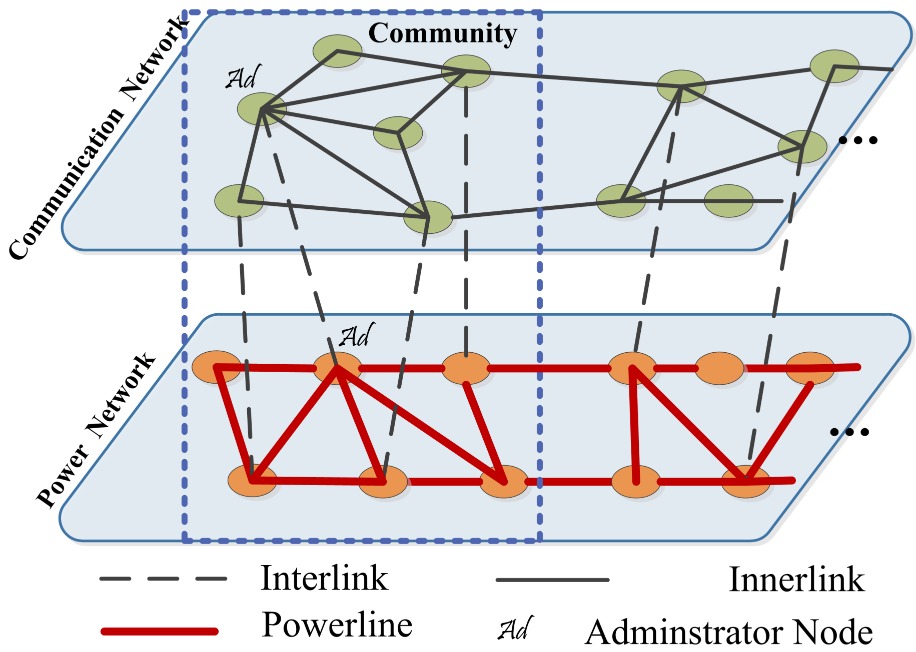

FIGURE 1. Model of the coupled network.

B. PROBLEM STATEMENT

For the coupled network, we pay attention to method how to couple two heterogeneous networks considering the modulation property of power grid for a smart grid. More specifically, in the interdependent model $G = (P, A^p, C, A^c, R)$ in (1), we discuss how to fill the value of the coupled matrix R according to given P, A^p, C and A^c, considering the modulation of A^p.

III. COUPLING ALGORITHM

In this section, we apply the classic community detection algorithm to the adjacency matrix to form modules in the first subsection. Then, we provide the coupling algorithm to couple the different nodes of pairwise communities in the second subsection. In each subsection, we provide an analysis of algorithms.

A. ASSEMBLE COMMUNITY

To weaken the condition of complete randomness, we apply the classic community detection algorithm to the power network [15]. Because A^p represents the power adjacency matrix, for node i, $d_i = \sum_j A^p_{i,j}$. The function δ has been defined as $\delta(u, v) = 1$ if $u = v$ and 0 otherwise. Let $m = \frac{1}{2} \sum_{i,j} A^p_{i,j}$ denote the number of total edges of the power network P. Assuming that node i belongs to the community c_i and all nodes have been divided into communities without overlap, we can use modularity Q to measure whether the community has assembled corrected nodes.

$$Q = \frac{1}{2m} \sum_{i,j} \left[A^p_{i,j} - \frac{d_i d_j}{2m} \right] \delta(c_i, c_j) \tag{2}$$

Some researchers have proposed a concrete algorithm of community detection with optimal performance [16]. They have achieved optimization of modularity by the heuristic computing ΔQ at the shorter computation time. Since the communication network has a topology that is similar to the topology of a power network in geographical locations [17], [18], we create the communities of a communion network with the same number of nodes and a more robust connection [19].

After a community has formed, the maximum range of c_k is defined as

$$ran(c_k) = \max\{dis^p_{x_i,x_j} or\ dis^c_{y_i,y_j}\}, \quad i, j \in c_k$$

Since the community c_i is only a structure connection, it does not contain an administrator node. We identify the administrator nodes using Ad_j in communities after the communities are established. With the vector parameters pu and pv, the community c^p_i matches the community c^c_j by

$$\begin{aligned} &dis_{ad^p_i, ad^c_j}(pu, pv) \\ &\quad = min \left\{ \left\| (ad^p_i)^T \cdot pu - (ad^c_j)^T \cdot pv \right\| \right\}, \quad \forall i, \forall j \end{aligned} \tag{3}$$

This match forms the pair of communities, as shown in figure 1. We use the assemble community algorithm (algorithm 1) to present the pairwise communities.

Time Complexity: If a network has n nodes and m edges, the algorithm complexity of the first step is $O(md \log n)$. Let d denote the depth of a dendrogram that describes the community. Identify the administrator needs $O(n \log n)$ using a quick sort in the second step. In the sparse network (e.g., smart grid), $m \sim n$ and $d \sim \log n$, an algorithm runs in $O(n\log^2 n)$. Therefore, the time complexity of algorithm 1 is $O(n\log^2 n)$.

Algorithm 1 Assemble Community

Input: The limited definitive interdependent network G

Output: Pair of communities

Use Q as a metric to form the community

Identify the administrator Ad_j for each community c_i within $ran(c_i)$

Obtain the parameters pu and pv and use (3) to connect the pairs of communities

B. INTER-MODULE COUPLING STRATEGY

In this subsection, we focus on the coupling method in pairwise communities. In smart substations, which are correlated with essential applications, often connect with more neighborhood nodes [20]. Similarly, the communication nodes, which are concerned with substations, are also tends to associate more communication nodes, because equipment needs to control, supervise, and run. According to this reality, we use positive degree coupling (PDC) algorithm (algorithm 2) to couple two heterogeneous communities. This algorithm indicates the high degree substations are prone to connect with the high degree communication nodes each other.

Assuming that we have community c_X^p including power nodes $X = \{x_1, x_2, \cdots, x_n\}$ with the weight vector $\omega(x_i)$. In a similar way, we have community c_Y^c including communication nodes $Y = \{y_1, y_2, \cdots, y_n\}$ and weight vector $\omega(y_j)$. Let RP stands for the random weighted permutation of X. We can get the inner connection between the two communities by PDC algorithm:

Algorithm 2 Positive Degree Coupling

Input: two communities c_X^p,c_Y^c and $|c_X^p| = |c_Y^c| = n$

Output: n pairs of coupled nodes

1: $Y' \leftarrow$ Sort Y according to the weight $\omega(y_j)$ in descending order.

2: Sum of weight of X, $totWeight \leftarrow \sum_{i=1}^{n} \omega(x_i)$

3: **for all** $k = 1$ to n **do**

4: $v \leftarrow$ randomly select an element in X with the probability $\omega(x_k)/totWeight$

5: $RP_k \leftarrow v$,$X \leftarrow X\backslash\{v\}$, $totWeight \leftarrow totWeight - \omega(x_k)$

6: add an edge in the two nodes (RP_k, Y_k')

7: $k = k + 1$

8: **end for**

9: **return** (RP, Y')

Algorithm 2 returns pairwise nodes with edges. The pairwise nodes originate from two heterogeneous networks. We use this information about nodes and edges to fill the matrix R in the model of the coupled network G to solve the problem.

From this algorithm, we obtain the random weighted permutation RP of X. In this permutation, the element with a large weight has a low excepted index [10].

Proposition: In the random weighted permutation RP, a node with a large weight has a lower expected index than a node with a smaller weight.

Proof: Let $E(X, v)$ be the expected index of the node v in the random weighted permutation RP. Then we have

$$E(X, v) = \frac{\omega(v)}{\sum\limits_{x \in X} \omega(x)} + \sum_{z \in X\backslash\{v\}} \frac{\omega(z)}{\sum\limits_{x \in X} \omega(x)} (1 + E(X\backslash\{z\}, v)) \tag{4}$$

Assuming that the weight of v_1 and v_2 satisfies $\omega(v_1) > \omega(v_2)$, we compare $E(X, v_1)$ with $E(X, v_2)$.

$$\begin{aligned} &E(X, v_1) - E(X, v_2) \\ &\quad = \frac{\{\omega(v_2)E(X\backslash\{v_2\}, v_1) - \omega(v_1)E(X\backslash\{v_1\}, v_2)\}}{\sum\limits_{x \in X} \omega(x)} \\ &\quad = \frac{\omega(v_2) - \omega(v_1)}{\sum\limits_{x \in X} \omega(x)} \end{aligned} \tag{5}$$

Due to hypothesis $\omega(v_1) > \omega(v_2)$, we obtain $E(X, v_1) < E(X, v_2)$ and the proposition holds.

Since the random algorithm is concerned with step 4 of algorithm 2, in the sequel, we employ the random algorithm to analyze the expected number of the node i with the probability $\omega(i) \Big/ \sum_{k=1}^{n} \omega(k)$ [21]. Let

$$I(x_i) = \begin{cases} 1 & \text{node } i \text{ is selected} \\ 0 & \text{else} \end{cases} \tag{6}$$

refer to the event in which node x_i is exactly selected. With the prerequisite that every loop is independent of the previous selection, we have expected the number

$$E(X) = E(\sum_n x_i) = \sum_n E(x_i) = \sum_n \Pr(x_i)$$

The probability of x_i is $P(x_i) = \frac{1}{n-i+1} \cdot \frac{\omega(x_i)}{\sum_{k=1}^{n-1+1} \omega(x_k)}$; therefore,

$$\begin{aligned} E(X) = \sum_n \Pr(x_i) = \frac{1}{n} \cdot \frac{\omega(x_1)}{\sum\limits_{k=1}^{n} \omega(x_k)} + \frac{1}{n-1} \\ \cdot \frac{\omega(x_2)}{\sum\limits_{k=1}^{n-1} \omega(x_k)} +, \cdots, + \frac{1}{2} \cdot \frac{\omega(x_{n-1})}{\omega(x_{n-1}) + \omega(x_n)} + 1 \end{aligned} \tag{7}$$

If the ordered weight $\omega(x_1) \geq \omega(x_2) \geq \cdots \omega(x_n)$, then the right part of $P(x_i)$ is a decreasing function. Thus we can achieve the results

$$\begin{aligned} E(X) &\geq (\frac{1}{n} + \frac{1}{n-1} + \cdots + 1) \cdot \frac{\omega(x_1)}{\sum\limits_{k=1}^{n} \omega(x_k)} \\ &\approx \frac{\omega(x_1)}{\sum\limits_{k=1}^{n} \omega(x_k)} (\ln n + O(n)) \end{aligned} \tag{8}$$

Although the expected number of the exact selection of node x is small, we can achieve the ordered permutation using the repeated trials. Algorithm 1 and algorithm 2 are integrated into a local positive degree coupling algorithm (LPDC) by input and output as we have previously presented. We express it as two parts to understand the LPDC.

IV. EXPERIMENT

Using experiments, we quantify two critical metrics. The results indicate that the LPDC is a more practical coupling approach than the completely random scheme. Since research on applicable simulation tools for both a power network and a communication network remain underway [22], [23], we use open NetworkX to construct a network and an experiment by Python [24].

A. SETUP AND METRIC

We create small world network to simulate the power with the NetworkX, as a power network has the remarkable feature of a small world [25]. In the classic small world network, nearest neighbors as well as reconnection probability are key parameters [24]. The nearest neighbors mean each node is joined with its k nearest neighbors. The reconnection probability implies reconnection probability of edge [24]. The experiment parameters of power network are 2, 3, 4 neighbor nodes as well as reconnection probability 0.2, 0.3, and 0.4, as neighbor nodes are not more than 4 in [25]. The power level permutations are 380 V, 500 V, 1000 V, 6000 V, 10 KV, 20 KV, 35 KV, 66 KV, 110 KV, 220 KV, 350 KV, and 500 KV. These values are randomly allocated to power nodes as one of the properties. Since the fault tolerance and self-healing ability are the distinguished characteristics of a smart grid, we use the power fault propagation (PFP) model to simulate a potential cascading procession [11].The nearest neighbors mean each node is joined with its k nearest neighbors. The reconnection probability implies reconnection probability of edge In the PFP model, the tolerance coefficient λ^p is 1.3. We select the top ten degree nodes to represent the administrator node. Regarding parameters pu and pv, we use a component of the node degree. Since most communication networks are observed to have the scale free property, we adopt the exponential factor between 2 and 2.6 [10], [18]. For the community detection method, we apply use the classic modularity Q as a metric by the fast heuristic method [16]. Different coupling strategies are designed to improve the robustness of the network and the facility of application. Let N represent the total nodes of an the interdependent network and N_0 denote the node number, which trigger the cascade and cause blackouts in the entire network. We employ the percentage P, which is defined as $P = N_0/N$ to measure different coupling algorithms. To a certain extent, this percentage reflects the ability to destroy the entire network. All experimental results are averaged over 50 independent trials.

B. PERFORMANCE

We compare the modularity Q value with different parameters of the reconnection probability and the nearest neighbors. Figure 2 shows the variation in the Q value according to different network scales. The nearest neighbors are 3, while reconnection probabilities are 0.2. Figure 2 reveals a large network has a large Q value. This finding indicates that a large network can develop a community with greater ease than a small network. The Q value nonlinearly increases when the node number increases. The reconnection probability 0.4 has large value than the reconnection probability 0.2 from the graph. Figure 2 reveals two gaps in the parameter reconnection probabilities. Note that the different gaps have minor influence on the Q value. The increasing trend of Q decreases when the network size increases. This observation also implies that a larger network can easily form a steady community.

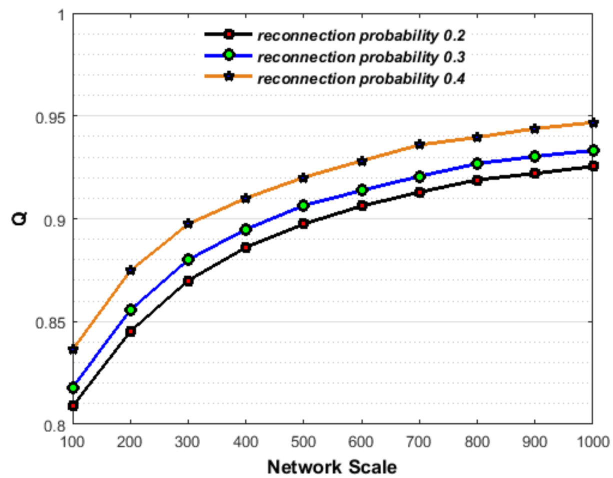

FIGURE 2. ***Q* with different reconnection probabilities.**

Figure 3 depicts the variation of the Q value with different nearest neighbors. The Q value slightly increases according to the network scale. From figure 3, we notice the sharp descent between 2 or 3 nearest neighbors and 4 nearest neighbors, when the reconnection probability is 0.3. This descent indicates that the key factor to the community is the nearest neighbors of a small world network. This observation can be a guiding principle to design a large-scale network for different power applications.

Table 2 provides the 50 Q values with reconnection probability 0.3 and 3 nearest neighbors when the node number is 200. Each number is an experimental result. Table 2 reveals that the Q value of 50 experiments with an average of 0.8556 and a standard deviation of 0.003865. This small standard deviation is another result, that is, the algorithm is relatively stable even if we do not intend to provide theoretical proof.

Figure 4 reveals a distinct trend of an average community number with respect to the network scale. With the reconnection probability 0.3, we achieve the average community number. An increase in the average community number follows the network scale because additional nodes are involved. The average community number in 4 nearest neighbors is smaller than the number of the others. Figure 5 reports the average

TABLE 2. Basic notations.

Q value in 50 trials									
0.8566	0.8552	0.8565	0.8528	0.8600	0.8594	0.8546	0.8597	0.8554	0.8607
0.8565	0.8584	0.8693	0.8662	0.8593	0.8626	0.8574	0.8562	0.8545	0.8524
0.8607	0.8544	0.8511	0.8554	0.8546	0.8548	0.8504	0.8534	0.8501	0.8525
0.8546	0.8572	0.8516	0.8532	0.8562	0.8523	0.8551	0.8515	0.8531	0.8550
0.8507	0.8548	0.8579	0.8501	0.8511	0.8555	0.8539	0.8531	0.8538	0.8565

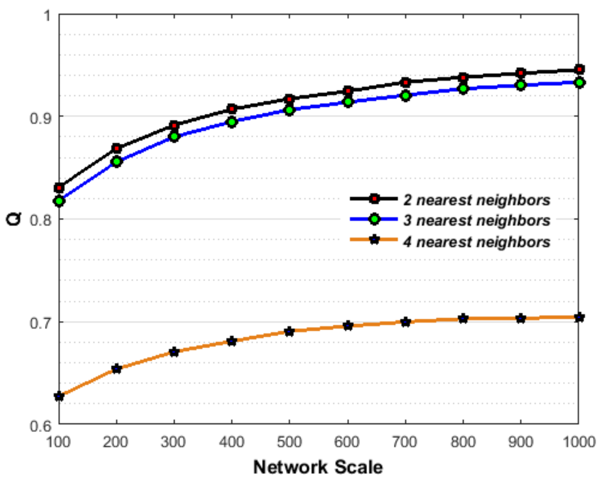

FIGURE 3. *Q* with different nearest neighbors.

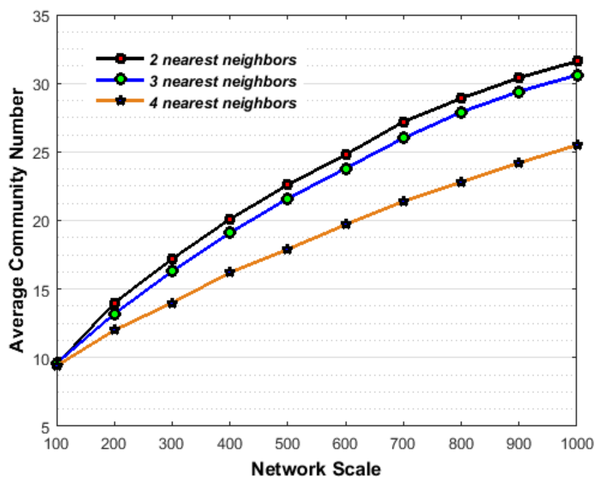

FIGURE 4. Average community number.

node number per community, which increases with different nearest neighbors. The average node number includes more nodes in the 4 nearest neighbors.

Regarding the coupling scheme, we compare three coupling strategies (i.e., complete random coupling (CRC), random coupling based on community (RCBC), and LPDC). For CRC, we couple a power network and a communication network in a completely random manner. RCBC intends to connect two different communities, and randomly couples nodes among each pair communities. Compared with LPDC, RCBC randomly connected many nodes based on algorithm 1. Note that the P value is a ratio. With this ratio, fault nodes can cascade the entire network instead of parts of

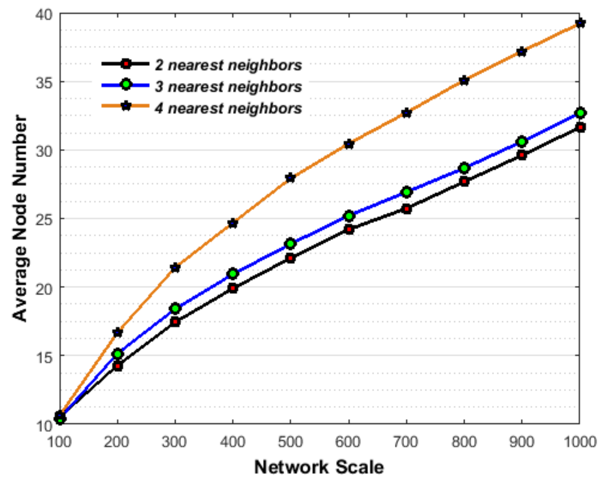

FIGURE 5. Average node number.

the network. The larger is the P value, the more robustness is the network.

As shown in figure 6, we obtain the smallest P value when the coupling scheme is completely random. With the LPDC strategy, P outperforms the other two coupling schemes. According to figure 6, the RCBC is better than the CRC because some faults can be tolerated in the inner community. The community has a greater inner connection in topology. For each coupling scheme, randomly fluctuates up and down along the average ratio, which is 0.2348, 0.3071, and 0.3436 for CRC, RCBC and LPDC, respectively. These results signify that the network scale has minimal concern with the P value.

Figure 7 describes the P value, which vibrates along the three average values 0.3223, 0.3889, 0.4270 for CRC, RCBC and LPDC, respectively. The P value is larger than the P value with figure 6 due to the different parameters of the network. A relationship with the model of cascade is observed [11]. Figure 6 and Figure 7 reveal that the coupled scheme based on the community is better than the completely random scheme for the small world network.

Figure 8 reports the runtime of the PRDC as well as LRDC algorithm with respect to different network scales. A related parameter is reconnection probability 0.3. The runtime increases with node numbers. The time is expressed in seconds. The nearest neighbors cause a large difference. The parameter of 4 nearest neighbors requires a larger amount of runtime than that of 2 nearest neighbors due to the network, which has a stronger connection and needs additional heuristic iterations to constitute steady community.

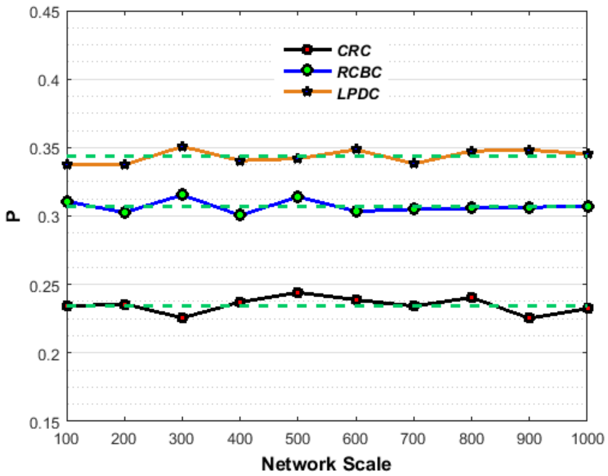

FIGURE 6. Different algorithms with 2 nearest neighbors.

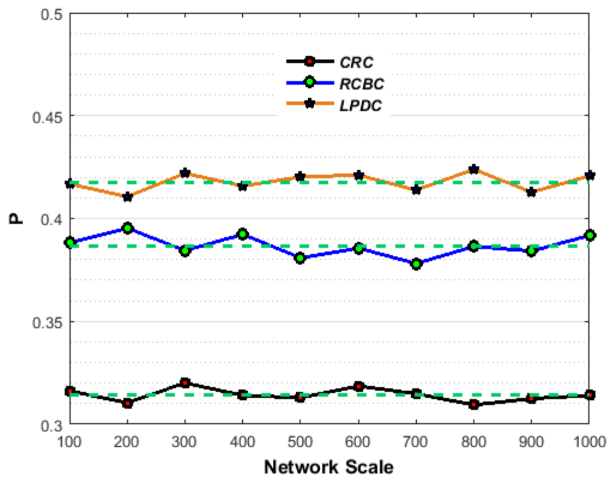

FIGURE 7. Different algorithms with 4 nearest neighbors.

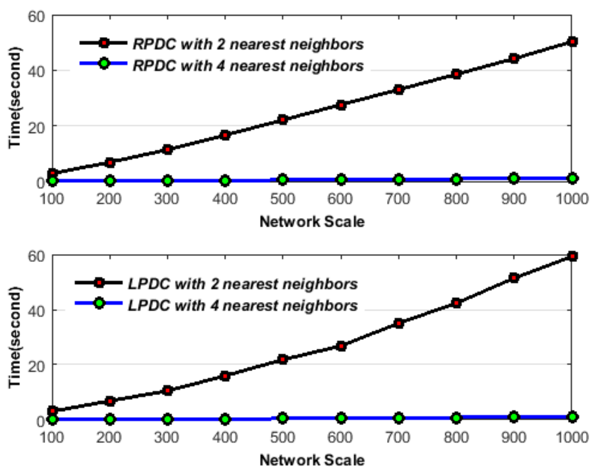

FIGURE 8. Running time.

V. CONCLUSION

In this paper, we focus on a coupling scheme for an the interdependent smart grid. We leverage the matrix to model the coupled network. Considering the significant modulation property of a smart grid, we proposed the local positive degree coupling (LPDC) strategy that is based on the community detection algorithm. To clarify the LPDC strategy, we have presented two related algorithms: the assemble community algorithm and the positive degree coupling algorithm. The experimental results indicate that LPDC has outperformed the complete random coupling method.

The proposed coupling strategy can be easily extended to a multilayer network for other researchers. This coupling method is easily applied to various networks with small changes, such as a cyber physical network and a social network. In future research, we will investigate the fault cascade from the viewpoint of pairwise nodes and quantitatively analyze an interdependent network based on the LPDC strategy.

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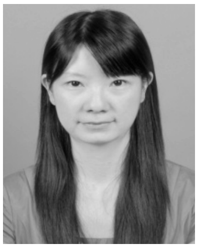

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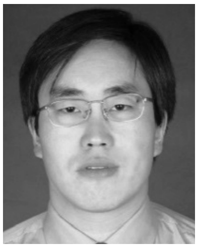

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