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Information Flow Modeling and Performance Evaluation of Communication Networks Serving Power Grids

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ABSTRACT A cyber-physical system (CPS) represents the coupling network between a communication network and a power grid. Information flow (IF) as the medium of communication networks has an important influence on the performance assessment of this type of coupling network. However, traditional IF models cannot be applied to CPS directly because they do not take CPS distinctive coupling effect and associated operational mechanism into account. In this paper, we propose an information flow model (IFM) based on graph theory and traffic dynamics considering the functional architecture and transmission mode in realistic CPS to bridge the gap mentioned above. In the IFM, congestion rate and loss rate are employed to assess the performance of communication networks serving power grids under different transmission strengths and modes. Moreover, an auxiliary model about CPS topology is constructed, which can generate more realistic CPS topology. Case studies on an IEEE 39-bus system reveal the transmission performance of CPS in detail. The IFM is exploited to detect critical nodes and compare the effects of node enhancement on IF transmission of networks. In addition, IFM is also applied to compare the transmission performances of six network topologies, including three basic complex networks and three community-based networks. The results demonstrate the effectiveness of the proposed model, and some suggestions are provided on performance improvement of IF transmission for CPS.

INDEX TERMS Cyber-physical systems, information flow, performance assessment, hybrid system model, overlapping community, transmission modeling.

I. INTRODUCTION

The enhanced coupling between power grids (PGs) and communication networks (CNs) has transformed traditional PGs into smart grids [1]. Recently, cyber-physical systems (CPS) have been increasingly applied to smart grids [2]. According to the CPS framework, CNs use Supervisory Control And Data Acquisition and Automatic Gain Control systems to implement the functions related to calculation, communication, and control, and assist PGs to perform safety scheduling [3]. Because a large quantity of electrical or non-electrical messages are transmitted through CNs, the services they carry exhibit multilevel and multidimensional characteristics, which require higher transmission performance [4].

A comprehensive system of modeling, quantization, and optimization is used for the analysis of electric current, which provides the theoretical basis for security and economical operation of PGs. CNs have similar requirements, such as network design [5], equipment selection [6], operational optimization [7], and abnormal online monitoring [8]. These requirements emphasize the real-time effectiveness of CNs, including the exchange of real-time information among dispatch centers, substations, and power plants, as well as the accuracy of dispatch commands at a critical moment [9]. Being the medium of transmission in CNs, information flow (IF) is the key aspect that should be investigated in the above research.

The traditional model of IF is mainly employed in the fields of Internet Technology communication or network science. In the field of Internet Technology communication, Yu *et al.* [10] proposed a three-layer control system by utilizing wireless information to perform energy management of renewable energy power plants. Cetinkaya *et al.* [11] exploited complex networks to analyze the transmission

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mode of IF in multi-layer networks, and used a multilevel graph evaluation framework to measure the robustness of the model. Enck *et al.* [12] established the TaintDroid analytical system to monitor the IF among smartphone users by tracking multiple data sources dynamically. In terms of the network science's field, Weng *et al.* [13] explored the relationship between community structures and communication modes in social networks and proposed a predictive method for future popularity of memes. Leclercq *et al.* [14] applied IF to traffic networks and used macroscopic fundamental diagrams to explain the traffic transmission in heterogeneous networks. Yang *et al.* combined IF with bio-inspired method to assess the evenness of network division [15] and the efficiency enhancement of transportation [16].

CNs serving PGs inherit the two core aspects of traditional communication, that is, person-to-person message exchange and open systems interconnection network model [3]. However, this kind of network also has its unique characteristics, such as using IEC61850 standardized information model, serving intelligent terminals, and having explicit operation [17]. Therefore, the logical nodes, protocol mapping, and data format for IF in the CPS, which are entirely different from the traditional IF model, are specified. Although the studies mentioned above provide the basis for modeling and the application scenarios for IF, they are not completely applicable to the CNs in CPS because they do not consider the operation mode of CNs serving PGs and the coupling effect between them. Therefore, they cannot directly reflect the phenomenon and mode of information transmission in the CNs of CPS, leading to poor interpretability.

Moreover, the interruption, delay, and error of information data are prone to active control failure and system state deterioration [18], [19]. In recent years, a series of blackouts were closely related to IF. In 2010, the Stuxnet virus attacked Iran's nuclear industry facilities [20]. The virus intercepted and modified the IF in the nuclear plant, thus disabling the control of the power plants. In 2015, power grids in Ukraine were severely damaged by cyberattacks [21]. By information injection, the attackers blocked the customer service system, which prevented users from receiving dispatch information and extended the blackout time. These security incidents also emphasize the importance of the IF model in CNs serving PGs.

By the IF model for CNs of CPS, we can detect the vulnerable time of information transmission, as well as the sensitive parts of systems. Based on that, the specific defensive schemes can be established to strengthen weak components and prepare the exclusive emergency measures more accurately. Therefore, based on graph theory and traffic dynamics, we establish an IF model (IFM) suitable for the CNs of CPS. The model considers the hierarchical coupling relationship, device information processing ability, and information transmission mode in CNs of CPS. We also define the congestion rate and loss rate to evaluate the performance of information transmission. Finally, we verify the feasibility and effectiveness of the IFM via critical nodes detection and different CNs topologies, and propose reference schemes for nodes enhancement and communication networking.

The main contributions of this paper are as follows.

(1) An information flow model is proposed to fit the CNs of CPS based on graph theory, traffic dynamics and transmission mode of CPS, which helps to understand the performance in actual CPS from the aspect of IF transmission.

(2) The CPS topology is constructed in accordance with multi-layer and overlapping community, which can provide a more realistic testbed to implement the proposed IFM.

(3) The congestion rate and loss rate are defined as the indexes to evaluate the CPS performance.

(4) The proposed IFM is tested from critical node detection and networking topology. The results show that both the critical node enhancement and network with reasonable multi-layer and community overlapping can contribute to the improvement of CPS transmission, and prove the model's effectiveness.

The rest of this paper is organized as follows. *Section II* introduces the mechanism of information flow in CPS. *Section III* presents the proposed IFM in detail. *Section IV* discusses the IF features in the IEEE 39-bus CPS model and the differences in IF performance among various communication networks in the IEEE 118-bus CPS model. Finally, *Section V* concludes the paper and reveals the direction of future work.

II. FEATURES IN COMMUNICATION NETWORKS SERVING POWER GRIDS

A. TOPOLOGY LAYERING OF COMMUNICATION NETWORKS

CNs are complex networks with the features of distributed acquisition and hierarchical transmission [22]. In order to adapt to service development, CNs can be represented as multi-layer networks, which are a family of graphs coupled by interconnections between nodes of different graphs [23]. Buldyrev *et al.* [24] firstly proposed the CPS multilayer networks model by Italy blackout caused by multilayer cascading failure. After that, some researchers applied this kind of networks to analyse CPS features, such as architecture [25], hierarchy [26], vulnerability [27] and so on. Generally, CNs can be treated as three-layer networks in terms of different functions. It is known that sensors group and primary equipment are responsible for collecting the information of PGs, which are regarded as the access part of CNs. As for transmission lines, optical cables have complex topology structure, i.e., the backbone part of CNs. The dispatching centers become the core part of CNs.

It is noted that the access part is tightly coupled with PGs, and their topologies are highly similar [22]. In order to make the process of IF transmission more intuitive, the following hypotheses are made:

(1) PGs are regarded as a single-layer network, since each part of PGs, including power generation, transmission, substation and distribution, has the same physical properties.

(2) CNs are divided into three layers in terms of functional differences, namely the access layer, backbone layer and core layer, which represent the access part, backbone part and core part of CNs, respectively.

So the architecture of CNs and PGs is shown in Fig. 1.

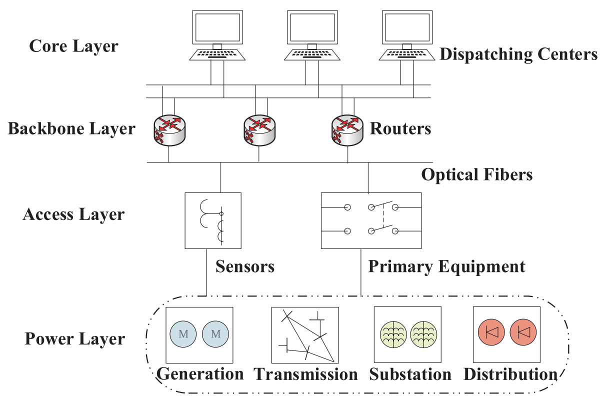

FIGURE 1. Architecture of CNs and PGs.

B. THE PHENOMENON OF OVERLAPPING COMMUNITY IN COMMUNICATION NETWORKS

In [24], [28], CNs in Italian and US meet the various services, and they reconstruct the existing network. It can be seen that CNs can be divided into multiple ring networks, and the internal nodes of a ring network are more closely connected than other outside nodes, which conforms to the concept of community structure. In addition, with the analysis of realistic topology [29], [30], there are crossover areas between the ring networks, which represent overlapping communities. The nodes in overlapping areas are often set as dispatching center. According to this rule, these topologies can be abstracted into a simple networking mode, as shown in Fig. 2. The whole complex network is superimposed and deformed by this mode.

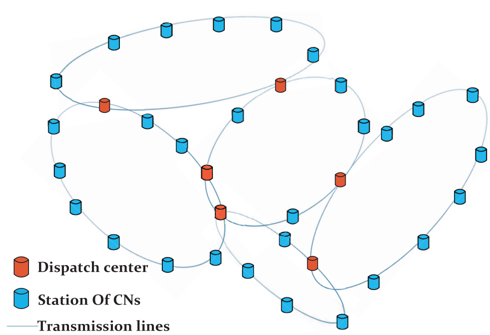

FIGURE 2. Networking mode in realistic CNs.

Therefore, the construction of CPS can be described briefly as follows. Access layer is the same as power layer due to their topological similarity, and they are full one-to-one coupling. Backbone layer can be built based on the overlapping nodes in access layer, and they are partial one-to-one coupling. By analogy, core layer can be constructed by the overlapping nodes in backbone layer, and they are one-to-many coupling.

C. INFORMATION FLOW IN COMMUNICATION NETWORKS OF CPS

Information in CNs of CPS refers to the corresponding electrical or non-electrical information generated by each subsystem. The flow of information represents the process of information acquired, forwarded, processed, and utilized in communication devices [4]. The IF determines the sender and receiver according to the functional requirements. Based on the IEC61850 protocol and routing policy, the information is standardized, and the most appropriate channel for transmission is selected [17]. Based on the functionality, the information can be generally divided into generic object-oriented substation event (GOOSE), sampled values(SV), manufacturing message specification (MMS), etc. They are utilized for performing steady state analysis, dynamic analysis, and optimization control.

Take Fig. 1 as an example of IF transmission in CNs. When a power network operates, the corresponding sensors in access layer map the value of the voltage and current samples into SV packets, and switch the position information and trip signal into GOOSE packets. These messages are uploaded to the dispatching centers in core layer via the routing devices and optical cables in backbone layer. After analysis and calculation, they transmit the protective signals to primary devices in access layer to implement scheduling control of PGs.

The number of SV and GOOSE packets will rise sharply during power failure, which increases the forwarding load. When this amount exceeds the forwarding threshold, information congestion or loss occurs, resulting in delays or errors in signals. Finally, it may hinder the timely handling of PGs faults, leading to further deterioration of network performance.

III. MODELING OF INFORMATION FLOW IN CNs SERVING PGs

In traffic dynamics, the change in the state of CNs is often described as cumulative or rate [31]. Cumulative is the net increment in node cached traffic within a given time. Rate is the reciprocal of the transmission time from the sender to the receiver. To simplify the IFM, this study makes the following assumptions.

(1) Channel influence is not considered when transmitting information because optical cables show better performance in transmission.

(2) Open shortest path first protocol is used to select the shortest path according to the congestion of each node at the previous moment.

(3) A hierarchical structure is used to reveal the realistic features of CPS [3]. Based on the functionality, the CNs are divided into 3 layers, that is, the core layer, backbone layer, and access layer.

(4) The forwarding abilities of the core layer, backbone layer, and access layer rank from high to low. Their buffer sizes also follow the same order.

The IFM is established in accordance with the above assumptions. The process is explained in detail below.

A. INFORMATION FLOW MODEL

1) BASIC MODEL

We model the CNs as an undirected graph that includes N_c nodes, and the generated information is represented by

$$flow_{ij}(t) = (f_{ij}(t), S_{ij}(t)) \tag{1}$$

where $f_{ij}(t)$ indicates whether node i sends an information packet to node j at time t. $S_{ij}(t)$ represents the node of $flow_{ij}(t)$ that arrives at time t. In addition, $f_{ij}(t)$ meets the criteria

$$\begin{cases} f_{ij}(t) = 1, & r < \lambda \\ f_{ij}(t) = 0, & r \geq \lambda \end{cases} \tag{2}$$

where r is a random number in the interval [0,1] and λ is the transmission probability. If r is lower than $\lambda, f_{ij}(t) = 1$, which means that node i sends an information packet to node j; otherwise $f_{ij}(t) = 0$.

For a single node, the information accumulation model at time t is given by

$$W_i(t) = W_i(t-1) + \sum_{j \neq k} Q_{jk}(t) - K_i(t) \tag{3}$$

where $W_i(t)$ is the number of information packets that node i needs to forward at time t, $K_i(t)$ is the number of information packets forwarded by node i, and $Q_{jk}(t)$ indicates if $flow_{jk}(t)$ arrives at node i at time t. It is defined as

$$\begin{cases} Q_{jk}(t) = 1, & if\ S_{jk}(t) = i \\ Q_{jk}(t) = 0, & if\ S_{jk}(t) \neq i \end{cases} \tag{4}$$

$S_{jk}(t) = i$ implies that $flow_{jk}(t)$ arrives at node i at time t.

In addition, we define B_i as the buffer size of node i. Therefore, the information packet loss is defined as

$$W_i(t) > B_i. \tag{5}$$

When inequation (5) is satisfied, node i will forbid the information input. In this case, loss occurs if information packets continue to arrive at node i.

2) TRANSMISSION STRENGTH

Generally, CNs transmit the periodic information in the steady state. When substation accidents or other unexpected events occur, IF will be in a continuous burst state, which is prone to congestion and loss [17]. Therefore, we define $\alpha(t)$ as the system transmission strength, which characterizes the generation of new information packets by the CPS at time t. The amount of information packets generated by the system is positively correlated with $\alpha(t)$ as

$$\lambda \propto \alpha(t) \tag{6}$$

where λ denotes the transmission probability. The larger the value of λ, the more new information packets the system generates at time t.

B. SYSTEM TRANSMISSION MODE

The CNs of CPS usually obtain real-time information of the PGs from access layer, and then transmits them to the dispatch center located at core layer through backbone layer. The control commands are reversed in this process. This shows that the senders and receivers are selected with the exception of backbone layer. Hence, this transmission mode exhibits a distinct "vertical" feature [32], namely, the vertical transmission mode (VTM).

Additionally, with improved intelligence level, operational information needs to be exchanged in real-time mode. With this flexibility, the senders and receivers can be any device, regardless of the layer. In this process, the IF shows more randomness [33] than in the VTM. Therefore, this mode is called random transmission mode (RTM).

Let the sender of $flow_{ij}$ be node i, the receiver be node j, and the node sets of the access layer, backbone layer, and core layer be V_a, V_b and V_c, respectively. In VTM, the sender and receiver of $flow_{ij}$ satisfy the following conditions:

$$\begin{cases} i \in V_a \\ j \in V_c \end{cases} \quad or \quad \begin{cases} i \in V_c \\ j \in V_a \end{cases} \tag{7}$$

In RTM, the sender and receiver of $flow_{ij}$ in the network satisfy the following conditions:

$$\begin{cases} i \in \{V_a \cup V_b \cup V_c\} \\ j \in \{V_a \cup V_b \cup V_c\} \end{cases} \tag{8}$$

C. EVALUATION INDEX

1) CONGESTION RATE

Congestion occurs when the number of information packets exceeds the forwarding capacity of the nodes. The congestion rate is defined as the ratio of the amount of remaining information packets at time t to the total amount of information packets. It is denoted by $\mu(t)$ and is expressed as

$$\mu(t) = \frac{\sum_{i=1}^{N_c} W_i(t)}{\sum_{t=0}^{T} \sum_{i,j \in N_c} f_{ij}(t)} \tag{9}$$

where N_c is the number of information nodes, and T is the simulation time.

Moreover, when the congestion rate exceeds the threshold, the CNs are in a congestion state, that is

$$\mu(t) \geq \mu_m \tag{10}$$

where μ_m is the threshold and is set to 0.1.

2) LOSS RATE

Information loss occurs when the amount of information packets stored in nodes exceeds their buffer size. Loss ratio is defined as the ratio of the amount of information packets lost by the entire system to the total amount of information packets before time t, and is expressed as $\eta(t)$.

$$\eta(t) = \frac{\sum_{t=0}^{T} Loss(t)}{\sum_{t=0}^{T} \sum_{i,j \in N_c} f_{ij}(t)} \tag{11}$$

where $Loss(t)$ denotes the number of lost information at time t.

Similarly, the threshold of loss rate is defined as η_m:

$$\eta(t) \geq \eta_m \tag{12}$$

where η_m is set to 0.1. When the inequation (12) is satisfied, it indicates that the information loss at this time is serious.

IV. CASE STUDY

A. IEEE 39-BUS CPS TOPOLOGICAL MODEL CONSTRUCTION

In this section, we build an auxiliary topology model using an IEEE 39-bus system as power layer. In accordance with *Section II.A* and *B*, the modeling method of topology should consider the multi-coupling networks and overlapping community, which can generate more realistic CPS topology.

The clique percolation method [34] is a popular approach for analyzing the overlapping community structure of networks. But its strict requirement for cliques is fully coupled networks, which results in ignoring a large number of overlapping nodes in CPS. As for the local community method, it expands community by randomly selecting seed nodes and combining by a fitness function, which makes overlapping nodes locate easily at border [35]. It is contrary to the principle of CPS overlapping nodes, that is, the dispatch center has large topological centrality. Both of the two methods cannot be utilized for CPS modeling.

Markov clustering algorithm (MCL) [36] is a detection method by the commutative processes of expansion and inflation of adjacency matrix, which can weaken the influence of non-community fully coupled structures, and produce overlapping areas rationally. Therefore, MCL is employed to construct the CPS topology, which is treated as the medium to represent performance of the proposed IFM. The process of MCL in this paper is illustrated in Fig.3.

In our simulation, the relevant parameters are set as follows. The similarity parameter is 0.3, self-multiplied index is 2, multiplication index is 1.5, node redundancy threshold is 2, and community threshold is 0.5.

Via this algorithm, the IEEE 39-bus system is partitioned and the specific results are shown in Table 1. It can be observed that there are five communities, and each has more than one overlapping nodes. Among them, community 3 contains the most overlapping nodes, i.e., nodes 15, 16, 17, 21, 24, and 27.

Based on *Section II.B*, the topology of access layer is the same as that of power layer [3]. And using these overlapping

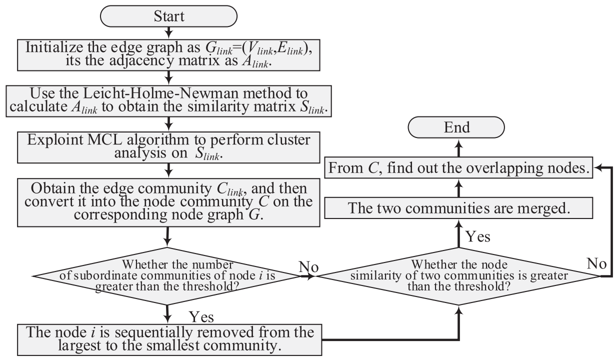

FIGURE 3. Flow chart of MCL.

TABLE 1. Community partitioning of IEEE 39-bus system.

Community	Member	Overlapping Nodes
1	1,2,4,5,6,7,8,9,11,30,31,39	4,6,11
2	4,6,10,11,12,13,14,15,32	4,6,11,15
3	3,15,16,17,18,19,20,21,24,27,33,34	15,16,17,21,24,27
4	16,21,22,23,24,35,36	16,21,24
5	17,25,26,27,28,29,37,38	17,27

nodes, the backbone layer and core layer are constructed in turn. Finally, the CPS network can be built, which includes 39 power nodes and 50 information nodes. The information nodes contain 39 access nodes, 9 backbone nodes, and 2 core nodes. The final CPS model is shown in Fig. 4.

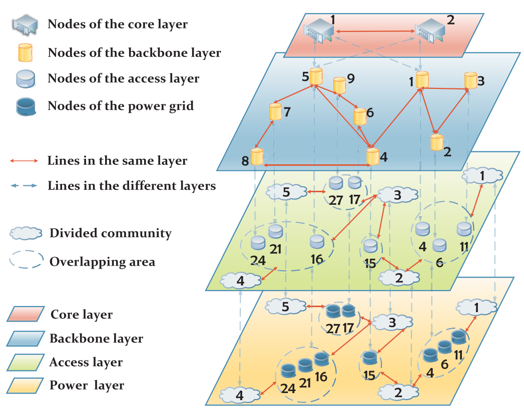

FIGURE 4. CPS model of IEEE 39-bus system.

B. INFORMATION FLOW FEATURES OF IEEE 39-BUS CPS MODEL

The IF of IEEE 39-bus CPS topological model is simulated in this section. The simulation time of the IFM is set to 150 s, and the transmission intensity α is increased from 0 to 3 in increments of 0.1. The simulation is performed 50 times for two kinds of transmission modes. The simulation results are shown in Fig. 5.

It can be seen from Fig. 5(a) that with the increase in α, the average congestion rate μ of CPS system slowly increases. It means that the more the information that is generated and transmitted simultaneously, the more congestion

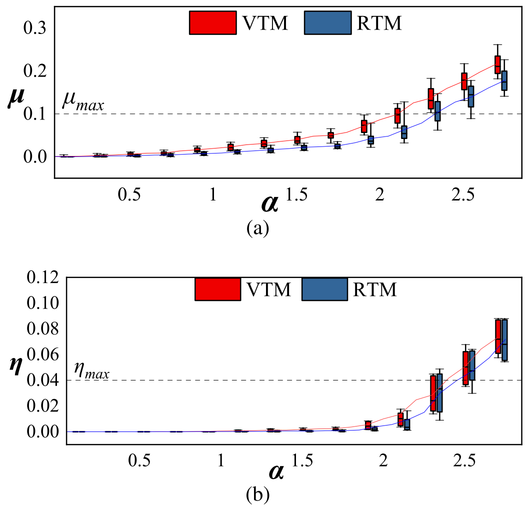

FIGURE 5. Evaluation indexes of IEEE 39-bus CPS system: (a) congestion rate and (b) loss rate.

the system is prone to. In VTM, the average μ reaches the threshold μ_m when $\alpha = 2.1$, whereas in RTM, the average μ reaches the threshold when $\alpha = 2.4$. It can be seen that the system can withstand greater transmission strength in RTM than in VTM. This is because in VTM, the sender and receiver of information are selected from the access layer and core layer, respectively, so that all information must pass through the backbone layer. The backbone layer and the overlapping nodes connected to them perform a large number of forwarding tasks. However, the sender and receiver of information in RTM can be selected from among three communication layers, which can largely prevents a single node from performing too many forwarding tasks, thereby reducing congestion.

In Fig. 5(b), the loss rate η of IEEE 39-bus CPS model also rises with increase in α, and the change is consistent with μ. The average η reaches the threshold η_m when $\alpha = 2.4$ in VTM; the corresponding value in RTM is $\alpha = 2.5$. This also shows that the system can withstand greater transmission strength with the RTM.

Compared with η, μ will reach the threshold at smaller transmission intensity. Because loss occurs only when information congestion is further deteriorated, that is, the amount of information packets received exceeds the node buffer size, the value of α when η exceeds η_m is more than that when μ exceeds μ_m. The loss rapidly worsens when the congestion is severe. From Fig. 5, for example, the average μ in VTM reaches μ_m when $\alpha = 2.1$; at the same time, however, the average η is 0.0036, which is much smaller than the threshold of 0.04. When $\alpha > 2.1$, the system is in a state of severe congestion, and the average η rises rapidly.

It can also be seen from Fig. 5 that the box becomes longer as α increases, which means the simulation results have a wider distribution range. Although the average μ when $\alpha = 2.1$ cannot reach μ_m in RTM, its maximum value exceeds the threshold. A similar result occurs with η in RTM.

In addition, when $\alpha = 2.3$, approximately one-sixth of η in VTM exceeds the threshold; when $\alpha = 2.7$, approximately four-fifths of η exceeds the threshold. Therefore, with increase in α, μ and η generally increase, and their distribution ranges are wider, which indicates that system congestion and information losses are more likely to occur, which may cause serious incidents.

C. INFORMATION DISTRIBUTION AND IFM-BASED CRITICAL NODES IN IEEE 39-BUS CPS MODEL

We analysed the information distribution of the simulation from the aspect of μ in *Section IV.B*. The contribution of each node to μ is shown in Fig. 6. The betweenness of some critical nodes is listed in Table 2.

TABLE 2. Betweenness of some critical nodes in IEEE 39-bus CPs system.

Rank	Betweenness	Node
1	399.5855	Access Node 16
2	254.756	Access Node 4
3	245.2992	Backbone Node 1
4	214.9455	Access Node 3
10	154.0293	Backbone Node 5
11	153.5183	Backbone Node 4
22	63.16176	Backbone Node 2

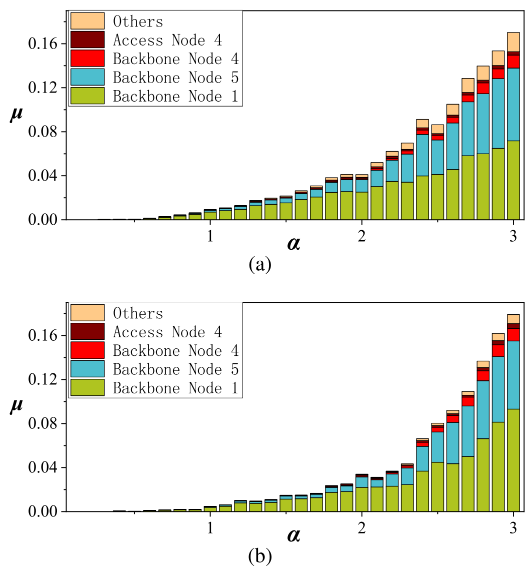

FIGURE 6. Contribution of each node to congestion rate in IEEE 39-bus CPS system: (a) VTM and (b) RTM.

According to Figs. 4 and 6, we find that the backbone nodes 1 and 5 are mainly responsible for the congestion, regardless of the transmission mode. With the high betweenness and connection with core layer, these two nodes are necessary for cross-layer information, especially for transmission in VTM. However, the backbone node 2 is not prone to congestion owing to its low betweenness and disconnection with core layer. The access node 4 is congested easily because it has high betweenness and connection with backbone layer, responsible for cross-layer transmission. Although the access nodes 3 and 16 have higher betweenness, they do not suffer from congestion easily because they do not perform the task of cross-layer transmission. Moreover, the contribution of other non-critical nodes to the congestion rises in RTM when compared with the VTM because the sender and receiver spread across 3 layers.

Thus, the high betweenness of nodes as well as the responsibility for cross-layer transmission enhances the possibility of congestion. In realistic CPS, these nodes typically represent provincial stations or some key routers that converge information from surrounding cities to the dispatching center. If the transmission abilities of these stations are strengthened, the system congestion would be relieved.

Taking IEEE 39-bus CPS as an example, we select some nodes with high betweenness or responsible for cross-layer transmission, and strengthen their abilities of IF transmission in order to investigate how the transmission performance changes. The transmission capacity of the selected node is increased by 1.5 times. To assess the improvement effect, the average proportion of congestion alleviation ($APCA$) is utilized as an index, represented by:

$$APCA = \frac{\sum_{t \in T} \frac{\mu_{original}(t) - \mu_{strengthen}(t)}{\mu_{original}(t)}}{T} \times 100\% \tag{13}$$

where μ is the congestion rate, $\mu_{original}$ is the original μ, and $\mu_{strengthen}$ is the μ with the increment of transmission ability. T is the total simulation time and t is the real time. Because the case of loss is similar to the congestion, the results of loss are not included. The simulation results are shown in Fig. 7.

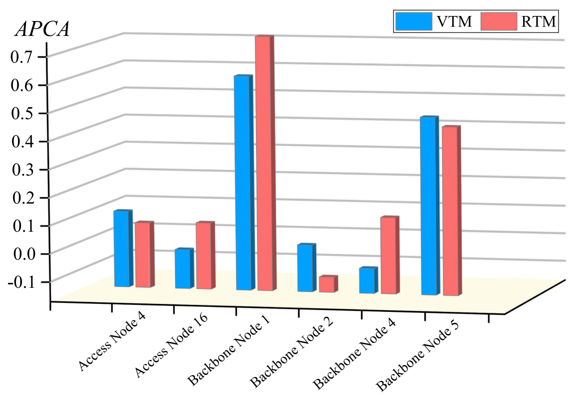

FIGURE 7. Comparison of average proportion of congestion alleviation based on nodes of strengthened ability.

It can be observed that after the access node 16 enhances the transmission ability the system congestion is not relieved in any transmission mode, but is worsened sometimes, such as its $APCA$ value is -3.0% in VTM. It is because the information transmitted to the coupling nodes increases, which aggravates the congestion when the access node 16 enhances its ability. The same situation occurs in backbone node 2, whose $APCA$ are -0.2% and -11.5% in VTM and RTM, respectively, as well as backbone node 4. Especially in VTM, the increased transmission ability shifts the forwarding

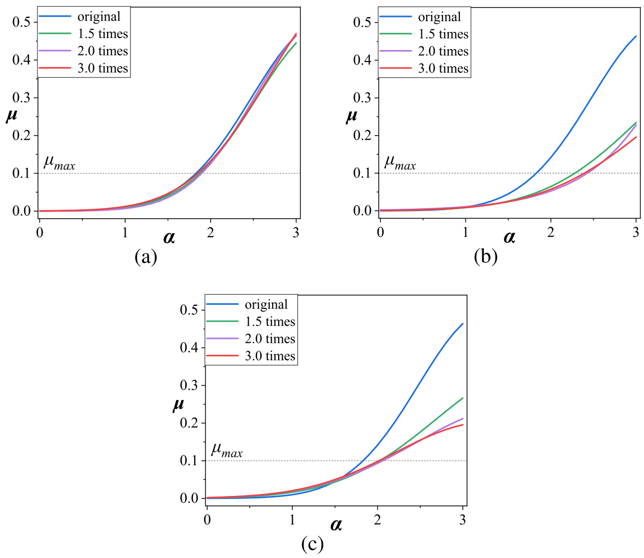

FIGURE 8. Comparison of cognestion alleviation in VTM in accordance with different forwarding abilities in nodes: (a) access node 4, (b) backbone node 1 and (c) backbone node 5.

burden to nodes coupled with core layer, such as backbone node 1, which deteriorates congestion. On the contrary, the upgrades of backbone nodes 1 and 5 are beneficial to alleviate information congestion. The $APCA$ of backbone node 1 can reach 60.0% and 74.3% in VTM and RTM, respectively, while the backbone node 5 can reach 46.5% and 43.2%, respectively. Since they have greater possibility to forward information due to coupling relationship and large betweenness, the node enhancement can accelerate the process of IF arrival. For the access node 4, its improvement can alleviate the system congestion, but the effect is relatively weak. Its $APCA$ are only 10.4% and 6.4% in VTM and RTM, respectively. For one thing, the original transmission ability of access node is relatively not strong. For another, access node is not the terminal of the uploading process, and the enhancement of its transmission ability will increase the congestion of other nodes.

Furthermore, the access node 4, backbone nodes 1 and 5 are selected to explore the relationship between the enhanced ratio and system congestion. Their transmission abilities are respectively set to 1.5, 2.0, and 2.5 times of the original values in VTM. The comparison results are shown in Fig. 8.

From Fig. 8, due to the ability enhancement of access node 4 the system congestion is not relieved much, and even is worsened when the transmission ability is enhanced more. When $\alpha = 2.1$ for instance, $\mu = 0.160$ in original state, while $\mu = 0.166$ in the ability enhanced by 2.0 times. The excessive forwarding makes the information transfer to other nodes too much, which aggravates the congestion of other coupling nodes. For backbone nodes 1 and 5, the system congestion is significantly alleviated after improving transmission ability. When μ reaches μ_m in case of backbone node 1, the α are 1.8, 2.3, and 2.5 in original state, 1.5 times and 2.5 times in enhancement, respectively.

TABLE 3. Statistical characteristics for six networks.

Statistical characteristics	PGs	ER		WS		BA		FAST		CP		MCL	
		CNs	CPS	CNs	CPS	CNs	CPS	CNs	CPS	CNs	CPS	CNs	CPS
Number of nodes	118	118	236	118	236	118	236	135	253	136	254	133	251
Number of edges	179	130	427	227	524	239	536	211	508	213	510	213	510
Average node degree	3.0339	2.2034	3.6186	3.8475	4.4407	4.0508	4.5424	3.1185	4.0119	3.125	4.0118	3.203	4.0637
Average path length	6.3087	7.4878	4.7025	3.9222	4.6044	3.1733	3.9713	6.0038	6.5855	6.3805	6.8153	5.8481	6.4972
Clustering coefficient	0.1651	0.0184	0.0398	0.7765	0.1717	0.7796	0.1713	0.1523	0.075	0.1597	0.0789	0.1717	0.0827

When $\alpha = 3.0$, in particular, the μ of the original state, 1.5 times, 2.0 times, and 2.5 times in improvement are 0.456, 0.241, 0.232, and 0.200, respectively, which means that the congestion decreases significantly.

Thus, according to IFM, the critical nodes can be found in the network. These nodes are often distributed in coupling areas, such as provincial stations, or in routers with higher betweenness. The transmission performance of CPS can be improved by enhancing the forwarding abilities of these stations and routers, especially the coupling stations in higher layer. In addition, if the congestion threshold of CPS is also increased, it can significantly improve the performance of IF transmission. Thus, they will give designers more choices in terms of efficiency and economy.

D. COMPARISON OF TRANSMISSION PERFORMANCE AMONG DIFFERENT COMMUNICATION NETWORKS

1) TOPOLOGICAL CHARACTERISTICS

To investigate the IF performance of CPS models built by different topological modeling methods, we compare three basic complex networks and three community-based networks. The basic complex networks include the random network method (ER) [37], small-world network method (WS) [38] and scale-free network method (BA) [39]. The community-based networks contain fast community search method (FAST) [40], clique percolation method (CP) [34], and MCL. Based on IEEE 118-bus system, the six methods are evaluated by constructing a CPS model considering multi-networks architecture. The modeling parameters are set as follows.

(1) ER: the connectivity value, m_{ER}, is 0.02; the node number of CNs, N_c, is 118, where the node numbers of the access layer, backbone layer, and core layer are 98, 18, and 2, respectively. The CNs are one-to-one coupled with the PGs.

(2) WS: the reconnection probability, P_{WS}, is 0.7. The number of information nodes and coupling relation are the same as that in the ER.

(3) BA: the connectivity value, m_{BA}, is 5; the reconnection probability P_{BA} is 0.8. The number of information nodes and coupling relation are the same as that in the ER.

(4) FAST: the maximum community modularity Q_{Fast} is 0.7. The node number of CNs, N_c, is 135, where the node number of the access layer, backbone layer, and core layer are 118, 15, and 2, respectively. The CNs and PGs are partially coupled one-to-one.

(5) CP: the maximum clique k_{CP} is 5 and reconnection probability P_{CP} is 0.6. The node number of CNs, N_c, is 136, where the node number of the access layer, backbone layer, and core layer are 118, 16, and 2, respectively. The CNs and PGs are partially coupled one-to-one.

(6) MCL: the relevant parameters are the same as that in *Section IV.A*. The node number of CNs, N_c, is 133, where the node number of the access layer, backbone layer, and core layer are 118, 13, and 2, respectively. The CNs and PGs are partially coupled one-to-one.

Note that the basic networks, i.e., ER, WS, and BA, adopt one-to-one coupling in this study, i.e., $N_c = N_p$. In the community-based networks, i.e. FAST, CP, and MCL, the access layer and power layer have one-to-one coupling, while other layers are constructed according to the community relationship. The statistical characteristics of the built networks are shown in Table 3, and their node degree distributions and sketches are shown in Fig. 9.

From Fig. 9 and Table 3, the degree distributions of ER and MCL are uniform without an evident power-law tail. Moreover, their average node degrees are low. In contrast, the degree distributions of SW and BA have distinct power-law tails, indicating that they have a large number of low-degree nodes and a small number of high-degree nodes. The CNs models constructed by SW and BA have relatively larger average node degree and clustering coefficients than the MCL and ER models. Conversely, the average path lengths of SW and BA are shorter.

It can also be seen that these three community-based networks do not have power-law tail distributions, meaning that their node degree distributions do not vary widely. Their difference lies in how they obtain the coupling nodes of each layer. The CNs constructed by the community-based methods have large average path lengths of 6.038, 6.3805, and 5.8481 for FAST, CP, and MCL, respectively. In both basic networks and community-based networks, the values of MCL's average node degree, average path length, and clustering coefficient are midway between the six methods.

2) COMPARISON OF TRANSMISSION PERFORMANCE BETWEEN MCL NETWORK AND BASIC COMPLEX NETWORKS

In this section, MCL network is compared with three basic complex networks in terms of transmission performance. The transmission intensity α is increased from 0 to 9.9 at intervals of 0.3. The average value of each evaluation index is obtained by repeating the simulation 20 times for the two transmission modes, and the results are shown in Figs. 10 and 11.

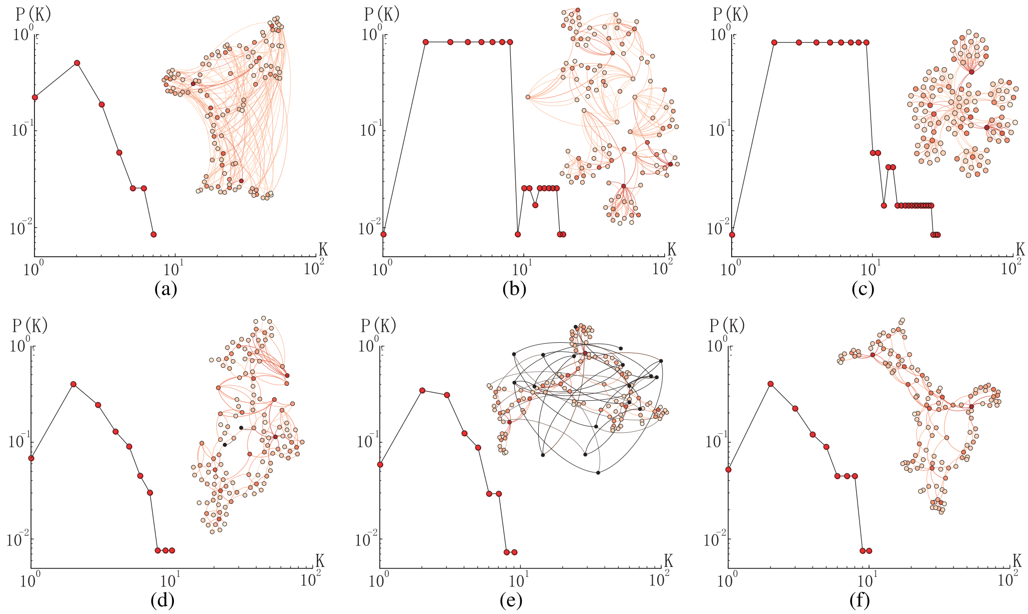

FIGURE 9. **Node degree distributions of the constructed CNs and their sketches: (a) ER, (b) WS, (c) BA, (d) FAST, (e) CP, and (f) MCL.**

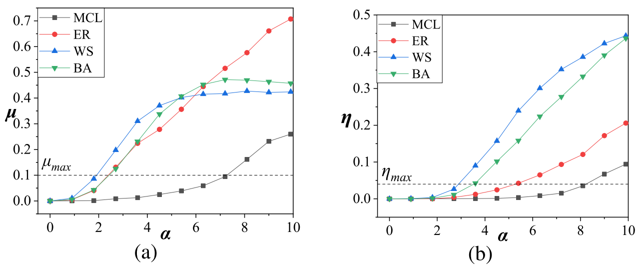

FIGURE 10. **Comparison of transmission performances in VTM with respect to (a) congestion rate and (b) loss rate.**

Fig. 10 shows the transmission performances of different networks in VTM. When $\alpha < 1.0$, the transmission efficiencies of the four models have little difference, and their μ and η are less than 0.05. When $\alpha = 2.1$, except for WS, μ has not reached μ_m in IEEE 118-bus CPS networks, whereas μ has reached μ_m in IEEE 39-bus CPS network. With regard to η, the small-size network also has poorer performance. It is shown that a larger network scale is likely to withstand greater transmission strength because the increase in the network scale provides more choices for information transmission path.

With increase in α, the average values of μ and η increase gradually in the four models. It can be seen that the WS network is the first to reach μ_m and η_m because its larger average node degree indicates that some nodes have numerous neighbors, thus enhancing the transmission tasks. Moreover, these nodes are mainly located in access layer with weak forwarding ability, thus reducing the network transmission efficiency.

In the cases of ER, BA, and MCL, the α corresponding to μ_m are approximately 2.3, 2.4, and 7.2, respectively; the same values are reported for η. Owing to the randomness of ER and BA, there are fewer backbone nodes in them that are connected with the core nodes, resulting in an impractical layout. Therefore, the information may arrive at the receiver by the access nodes with poor forwarding ability. Conversely, MCL networks set the backbone nodes that connect with the core nodes in each community. This hierarchical structure improves its forwarding efficiency.

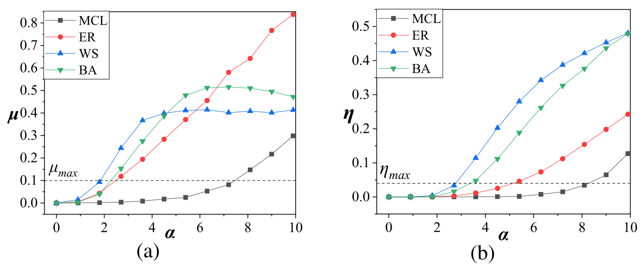

FIGURE 11. **Comparison of transmission performances in RTM with respect to (a) congestion rate and (b) loss rate.**

The comparison of transmission performances in RTM is presented in Fig. 11. The α values of the ER, WS, BA, and MCL models that correspond to the threshold value of μ are 2.5, 1.8, 2.3, and 7.5, respectively. The α values of the ER, WS, BA, and MCL models corresponding to the threshold value of η are 5.2, 3.7, 3.6, and 8.3, respectively. This also proves that MCL can withstand greater transmission strength than the non-community methods.

It should be noted that in RTM, μ will decrease at a specific value of α in the WS and BA networks. For example, from Fig. 11(a), μ is 0.515 for the BA network when $\alpha = 7.2$, while it decreases to 0.472 when $\alpha = 10.0$. This is mainly because in RTM, the information sender can exist in various layers. If an information sender is located at a lower layer, the probability of persistent congestion at low-level nodes is higher owing to weak forwarding ability. When α rises to a certain value, the increase in the loss exceeds that in congestion, leading to decrease in μ.

In short, MCL model has the best transmission ability. Owing to low average node degree, ER also has relative better transmission performance. However, in WS and BA, the underlying information cannot be quickly uploaded to the upper layer because the distribution of coupled nodes is unreasonable in cross-layer transmission.

3) COMPARISON OF TRANSMISSION PERFORMANCE BETWEEN MCL NETWORK AND COMMUNITY-BASED NETWORKS

In this section, MCL network is compared with two community-based networks, and the simulation results are presented in Figs. 12 and 13.

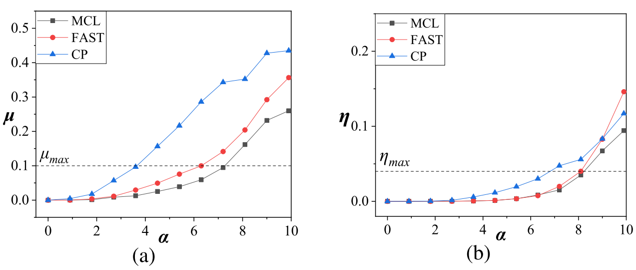

FIGURE 12. **Comparison of transmission performances in VTM for community-based networks: (a) congestion rate and (b) loss rate.**

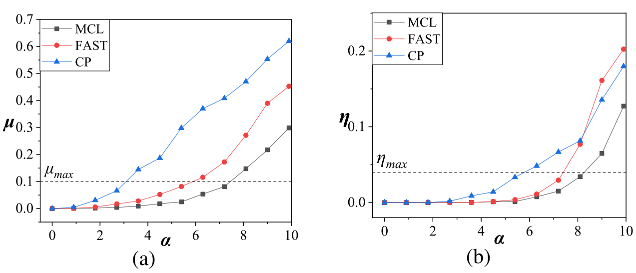

FIGURE 13. **Comparison of transmission performances in RTM for community-based networks: (a) congestion rate and (b) loss rate.**

Fig. 12 shows the transmission performances of different community-based networks in VTM. When $\alpha = 2.1$, μ is 0.0035, 0.0185, and 0.0014 for FAST, CP, and MCL, respectively, which are significantly lower than μ_m of the non-community networks under the same circumstance. With increase in α, the average values of μ and η also increase gradually for three networks in VTM.

The values of α corresponding to the threshold value of μ of the FAST, CP, and MCL are 6.3, 3.6, and 7.2, respectively. The results of η are similar to μ, the discussion of which is omitted owing to space limitation. Overall, the community-based networks show better transmission performance than the non-community networks, mainly because of their appropriate hierarchical structure.

Moreover, the comparison results show that the CP network has poorer performance than FAST. This is because the CP network has high requirement for a fully coupled clique. However, there are fewer sub-networks that satisfy this requirement, and the overlapping nodes are scattered and cannot cover all communities well. The MCL network can weaken the limitation of full coupling and distribute them over a reasonable area, which allows it to bear the maximum α among the six models.

Fig. 13 shows the comparison of transmission performances in RTM. It can be seen from Fig. 13(a) that the values of α corresponding to the threshold values of μ of the FAST, CP, and MCL are 6.0, 3.3, and 7.5, respectively. From Fig. 13(b), the values of α corresponding to the threshold values of η of the FAST, CP, and MCL are 7.3, 6.0, and 8.3, respectively. The community-based models are generally better than those non-community models and they can demonstrate greater transmission strength, especially the MCL model has the strongest capacity for withstanding transmission tasks.

In summary, the MCL model has the best information transmission ability. Compared with other community-based methods, i.e., FAST and CP, the MCL model considers the nature of the overlapping communities and overcomes the uneven distribution of the overlapping nodes as well as the irrationality of the overlap, which makes the transmission better. In addition, compared with the FAST and CP models, the relatively high average node degree and clustering coefficient provide the MCL model with more path selection during transmission, which can effectively avoid the overloading of a single node. The relatively low average path length allows it to reach the receiver more quickly, and facilitates the rapid completion of transmission tasks.

4) COMPARISON OF TRANSMISSION PERFORMANCE BASED ON EUROPEAN HIGH VOLTAGE TRANSMISSION NETWORK

Due to the larger network size and more complexity, the European high-voltage transmission network is selected to test the performance of IFM for large networks. This network has 1354 stations, in which there are 260 power generators, and 1991 high-voltage lines [41]. Its structure is shown in Fig. 14. Taking it as the power layer, the CPS networks are constructed based on six topological algorithms mentioned above. And their IF transmission efficiencies are evaluated by IFM. The simulation settings are unchanged, except that the transmission intensity α is increased from 0 to 22.5 at intervals of 2.25. The simulation results are shown in Figs. 15 and 16.

It can be seen that the larger the scale, the greater transmission intensity networks can withstand, which is consistent with the results obtained by the 118-bus case. When $\alpha = 12.0$ for example, the μ and η of six networks based on this large network are far from the thresholds, while they exceed the thresholds under 118-bus power layer when $\alpha = 8.0$.

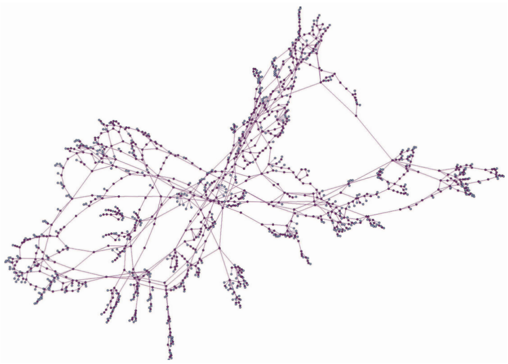

FIGURE 14. Visualising the European high-voltage transmission network.

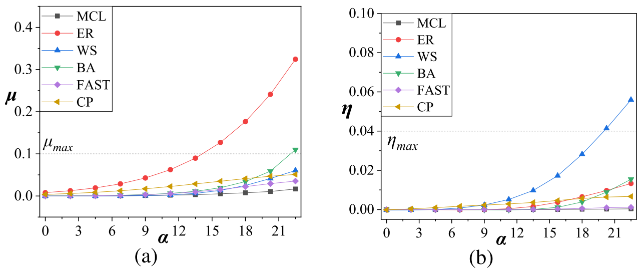

FIGURE 15. Comparison of transmission performances in VTM for six CPS 1354-bus networks: (a) congestion rate and (b) loss rate.

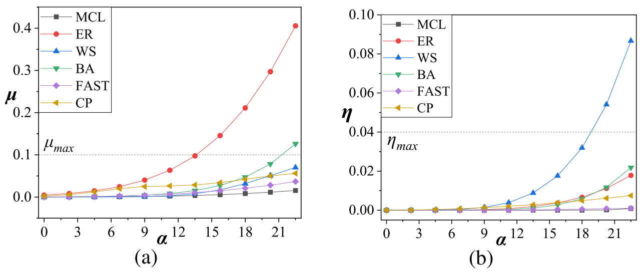

FIGURE 16. Comparison of transmission performances in RTM for six CPS 1354-bus networks: (a) congestion rate and (b) loss rate.

Furthermore, the community-based networks are generally superior to the non-community networks at the aspect of transmission performance. When $\alpha = 20.25$ in VTM for instance, the μ of ER, WS, BA, FAST, CP, and MCL networks are 0.176, 0.025, 0.034, 0.022, 0.041, and 0.008, respectively. And the MCL has the best transmission performance among six networks under VTM and RTM. When $\alpha = 22.5$, the μ of MCL only is 0.015 and its η is 0.001, both of which are much smaller than the thresholds.

In short, with the help of the proposed IFM, we find that CNs can obtain higher transmission efficiency if its topology has the features as follows.

(1) The node degrees of most coupling stations are low;

(2) CNs are constructed in the form of backbone rings, and there are overlapping areas between them;

(3) The overlapping areas have large centrality, and the stations or routers in these areas are set as the backbone nodes.

TABLE 4. Rank of some critical nodes in 1354-bus CPs system.

Rank of congestion and loss	Nodes
1	Backbone Node 105
2	Backbone Node 2
3	Backbone Node 38
4	Backbone Node 27
5	Backbone Node 66

Moreover, the information distribution of this MCL network is analyzed. And some nodes with greater contribution to congestion and loss of networks are list in Table 4.

We design three schemes to improve the networks performance to 1.5 times in terms of the transmission ability. The three schemes include: A) backbone node 105; B) backbone nodes 105 and 2; C) backbone nodes 105, 2 and 38. The transmission intensity α is increased from 0 to 40.5 at intervals of 4.5. *APCA* is utilized to evaluate the improvement under each scheme. The results are shown in Fig. 17.

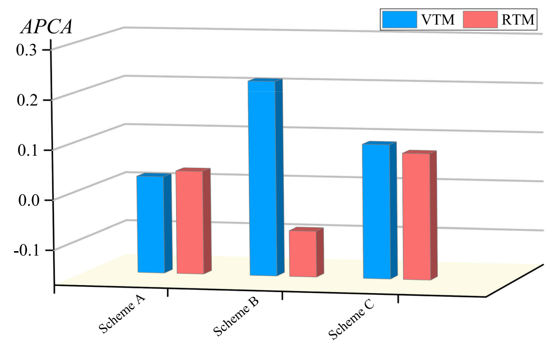

FIGURE 17. Comparison of average proportion of congestion alleviation based on different schemes.

It can be seen that selecting the appropriate node set for ability improvement can achieve better transmission efficiency. But too many nodes may lead to the opposite results. In VTM for example, the *APCA* of Scheme B is 22.2%, while in Scheme C it is only 10.0%, even though the number of nodes in Scheme C is more than that in Scheme B. And the scheme with fewer nodes does not mean the less improvement. In RTM for instance, the *APCA* of Scheme A is 3.8%, while in Scheme B it is −7.7%. Therefore, it is necessary to formulate the improvement strategy according to specific requirements and budgets.

For transmission efficiency improvement from ability enhancement of critical nodes, we can draw some conclusions as follows.

(1) The critical nodes are often responsible for cross-layer transmission or with large betweenness;

(2) Improving the transmission ability of a single critical node appropriately can relieve the overall congestion of networks;

(3) Proper number of updated nodes can improve the performance of networks, but too many or too few nodes may be less helpful for improvement.

V. CONCLUSION

With the deep coupling of CNs and PGs, it is of great importance to consider the factors affecting communication in CPS performance assessment. Based on graph theory and traffic dynamics, we construct a model for IF, called the IFM, in accordance with the operational mechanism of realistic CNs serving PGs. The IEEE 39-bus system was utilized to investigate the IFM performance with its coupled CNs model. Then, the IFM was applied to analyze the effect of critical nodes on IF performance, as well as information transmission features in different topological models. The results show that the proposed IFM can detect these critical nodes more precisely which have great effect on IF transmission, and the ability enhancement of these nodes can significantly improve the network performance. Also, the IFM can be utilized to evaluate the transmission performance of CNs from the topological perspective, which indicates that the hierarchical structure and overlapping communities have a significant effect on the IF in CPS. The results validate the effectiveness and practicability of the proposed IFM, which helps planners to design network architecture and improvement schemes economically and efficiently. In our future work, we will consider cyber-attacks as well as gaming behavior in information security, which can affect the accuracy of the built model. Also, the social structure would influence the topological architecture of CPS.

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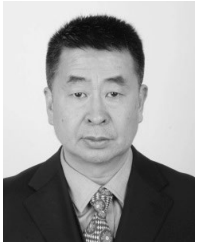

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