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An efficient and fast computing power resource scheduling method for smart distribution networks based on hypergraph convolution networks

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Smart distribution networks (Smart DNs) serve as a key component of the intelligent digital infrastructure for new power systems [1]. Currently, the scale of heterogeneous data transmitted in Smart DNs has increased exponentially due to the large proportion of new energy units and new power electronic devices connected to DNs [2]. Moreover, a series of compute-intensive applications has emerged, such as distributed energy resource management and intelligent robot inspection, which require not only real-time and reliable data transmission, but also sufficient computing power to make correct and timely decisions [3]. To meet the needs of flexible and stable operation of Smart DNs and ensure continuous new energy integration, it is urgent to expand the computing, communication, and storage resources and capabilities of heterogeneous nodes for building large-scale ubiquitous computing power networks (UCPNs). Although UCPNs have many benefits, it is very challenging to realize flexible scheduling of computing power resources under the performance requirements of massive and diverse compute-intensive tasks.

•UCPNs in Smart DNs are the cyber-physical interdependent systems [4]. Computing and communication resource scheduling may occur between nodes that are on the same power line. These relationships of similar spatial distribution and high position dependency need to be characterized in UCPNs to obtain an accurate network state and accelerate the speed of node selection.

•Computing resources are distributed and finite. To accomplish a computing task, communication and computing resources may exist in the form of groups. However, these resources are independent among nodes. Environmental impacts may lead to nodes with sufficient computing power but limited communication resources. Therefore, the resource scheduling scheme should point out the differences in resource provisioning capacities and potential group relationships among heterogeneous nodes to enhance scheduling efficiency and responsiveness.

To solve these challenges, we propose an efficient and fast computing power resource scheduling method for UCPNs in Smart DNs. Our main contributions are as follows. (1) A novel and unified hypergraph modeling method is proposed for UCPNs in Smart DNs to capture the high-order relationships, enabling faster node selection and resource mapping. Specifically, hyperedge groups using cyber-physical interdependence, connectivity features, k-hop neighbors, and multi-dimensional resource attributes are constructed. (2) A hypergraph convolutional attention network (HGcov-atten) for computing resource scheduling is proposed. Hypergraph convolution embeds four high-order relationships into nodes via convolution operators to generate node computing power evaluation values, selecting top Q nodes as targets. Moreover, the graph attention mechanism weights neighbors by transmission rate, delay, and reliability of links to find the optimal next hop. By repeating this process, the end-to-end paths from the source to targets are generated.

Hypergraph construction for UCPNs in smart DNs. The UCPN hypergraph is defined as $\mathcal{G} = (\mathcal{V}, \mathcal{E}, \boldsymbol{H})$, where $\mathcal{V}$ is the set of computing nodes, $\mathcal{E}$ is the hyperedge set, and $\boldsymbol{H}$ is the incidence matrix. As shown in Figure 1, the hyperedge set $\mathcal{E}$ is composed of four types of hyperedge groups, namely cyber-physical interdependence ($\mathcal{E}_{\rm ind}$), connectivity feature ($\mathcal{E}_{\rm con}$), k-hop neighbors ($\mathcal{E}_{\rm hop}$), and multi-dimensional resource attributes ($\mathcal{E}_{\rm res}$). $\mathcal{E}_{\rm ind}$ groups computing nodes on different power lines to model the spatial and positional dependencies of UCPN nodes. $\mathcal{E}_{\rm con}$ clusters nodes with varying connectivity, leveraging the communication modes between node pairs to reflect whether a vertex has more next-hop options. $\mathcal{E}_{\rm hop}$ categorizes the k-hop neighbors of a certain vertex v, aiming to identify the related nodes via k-hop reachable positions. $\mathcal{E}_{\rm res}$ contains computing nodes in different intervals and models the correlation among heterogeneous nodes with differentiated resource provisioning capabilities at the group level. The incidence matrix $\boldsymbol{H}$ is constructed by direct concatenation: $\boldsymbol{H} = \boldsymbol{H}_{\rm ind}||\boldsymbol{H}_{\rm con}||\boldsymbol{H}_{\rm hop}||\boldsymbol{H}_{\rm res}$, where

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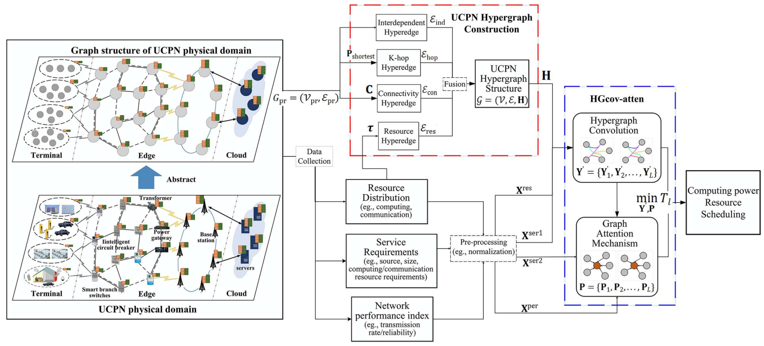

Figure 1 (Color online) Framework of computing power resource scheduling of UCPNs for Smart DNs.

$\cdot||\cdot$ is a matrix concatenation operation, $\boldsymbol{H}_{\text{ind}}$, $\boldsymbol{H}_{\text{con}}$, $\boldsymbol{H}_{\text{hop}}$, and $\boldsymbol{H}_{\text{res}}$ are incidence matrices of $\mathcal{E}_{\text{ind}}$, $\mathcal{E}_{\text{con}}$, $\mathcal{E}_{\text{hop}}$, and $\mathcal{E}_{\text{res}}$, respectively.

Hypergraph convolutional attention network for computing power resource scheduling. Based on the UCPN hypergraph, we design a hypergraph convolutional attention network (HGcov-atten), which integrates hypergraph convolution and graph attention mechanism. In the hypergraph convolution, the inputs are incidence matrix $\boldsymbol{H}$, attributes and resource requirements of tasks $\boldsymbol{X}^{\text{ser1}}$, and vertex resource features $\boldsymbol{X}^{\text{res}}$. The hypergraph convolution operation is

$$\boldsymbol{Y}^{(t+1)} = \sigma_{\text{sigmoid}}(\boldsymbol{D}_v^{-1/2}\boldsymbol{H}\boldsymbol{W}\boldsymbol{D}_e^{-1}\boldsymbol{H}^{\text{T}}\boldsymbol{D}_v^{-1/2}\boldsymbol{X}^{(t)}\boldsymbol{\Theta}^{(t)}), \tag{1}$$

where $\boldsymbol{D}_v$ is the vertex degree matrix, $\boldsymbol{D}_e$ is the hyperedge degree matrix, $\boldsymbol{W}$ is the identity matrix, $\boldsymbol{X}^{(t)}$ and $\boldsymbol{Y}^{(t+1)}$ are input and output of hypergraph convolution layer t, $\boldsymbol{\Theta}^{(t)}$ is the coefficient of the Chebyshev polynomial, and the sigmoid activation function is defined as $\sigma_{\text{sigmoid}}(\cdot)$.

The output $\boldsymbol{Y} = \{\boldsymbol{Y}_1, \boldsymbol{Y}_2, \ldots, \boldsymbol{Y}_L\}$ is composed of the evaluation values of all computing nodes within k hops from task sources, where L is the number of computing tasks. If only the computing node with the largest value is selected as the target based on $\boldsymbol{Y}$, the dynamic matching between the task and the network performance during the transmission process from source to target will be ignored. Therefore, we sort the elements in $\boldsymbol{Y}$ in descending order, select the top Q computing nodes with the highest evaluation values as the target set, and finally output matrix $\boldsymbol{Y}' = \{\boldsymbol{Y}_1', \boldsymbol{Y}_2', \ldots, \boldsymbol{Y}_L'\} \in \mathbb{R}^{L\times Q}$.

In graph attention mechanism, the inputs are target set $\boldsymbol{Y}'$, communication requirements of tasks $\boldsymbol{X}^{\text{ser2}}$, and network performance features $\boldsymbol{X}^{\text{per}}$. Through the LeakyReLU activation function, the absolute attention coefficient of node n to the source v_0 is obtained:

$$\mu_{v_0,n} = \sigma_{\text{LeakyReLU}}(\overrightarrow{\boldsymbol{a}}[\boldsymbol{W}_{\text{att}}\boldsymbol{x}_{v_0}^{\text{per}}||\boldsymbol{W}_{\text{att}}\boldsymbol{x}_n^{\text{per}}]), \tag{2}$$

where $||$ is the matrix concatenation operation, $\boldsymbol{W}_{\text{att}}$ is a shared weight matrix, and $\overrightarrow{\boldsymbol{a}}$ is the weight matrix of the feedforward neural network. To facilitate comparison of coefficients across different computing nodes, the softmax function is used to normalize the absolute attention coefficients, and the relative attention coefficient of node n to the source v_0 is expressed as

$$\tau_{v_0,n} = \sigma_{\text{softmax}}(\mu_{v_0,n}) = \frac{\exp(\mu_{v_0,n})}{\sum_{v_0\neq v, v\in\mathcal{N}_{v_0}}\exp(\mu_{v_0,v})}, \tag{3}$$

where $n \in \mathcal{N}_{v_0}$, $\mathcal{N}_{v_0}$ is the set of first-order neighbors of the source v_0 (including v_0). $\tau_{v_0,n}$ is the probability that the neighbor node n of the source v_0 belongs to the optimal next hop. We select the neighbor node with the highest probability from $\boldsymbol{\tau}_{v_0}$ as the optimal next hop. The optimal next hop is regarded as the central node of the next attention layer. Therefore, we take the output of each attention layer as the intermediate result and mainly focus on the establishment of the optimal end-to-end path $\boldsymbol{P} = \{\boldsymbol{P}_1, \boldsymbol{P}_2, \ldots, \boldsymbol{P}_L\}$.

Experimental results. To verify the effectiveness of the HGcov-atten, we compare it with four benchmarks, and implement ablation experiments and parameter sensitivity. Compared with benchmarks, the average accuracy of the HGcov-atten is improved by a maximum of 22.48%. Specific details can be found in Appendix F.

Conclusion. We propose a hypergraph modeling method of UCPNs for Smart DNs, aiming to capture the high-order topological connections and differentiated resource provisioning capabilities among UCPN vertices. Based on the proposed UCPN hypergraph structure, we design an efficient computing power resource scheduling algorithm to enhance resource utilization by orchestrating the computing and communication resources of heterogeneous nodes.

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Supporting information Appendixes A–F. The supporting information is available online at info.scichina.com and link.springer.com. The supporting materials are published as submitted, without typesetting or editing. The responsibility for scientific accuracy and content remains entirely with the authors.

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