State Estimation of Energy Internet Using SCADA and PMU Data Based on Graph Convolutional Networks

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***Abstract*—The real-time state estimation is crucial to guarantee the stable operation of energy Internet (EI) which has variable loads and distributed power generations. Therefore, this paper proposes a real-time transient state estimation method for EI based on graph convolutional networks (GCN). Using data of SCADA and limited phasor measurement unit (PMU), the GCN in the proposed method fuses the heterogeneous data of EI buses with the adjacency matrix that represents the topology of EI. Then the transient states of EI buses without PMU measurement are estimated by SCADA data and adjacent PMU data through the training of GCN model. The case study on the simulation data of an IEEE 9 bus system that considers fault injection and disturbances verifies the effectiveness of the proposed approach. The result shows that the proposed approach achieves fast and accurate state estimation of all EI buses during the transient process of faults and disturbances.**

***Index Terms*—Energy Internet, graph convolutional networks, phasor measurement unit, state estimation.**

I. Introduction

With the ability of absorbing distributed energy resources and achieving effective energy management, the research on energy Internet (EI) develops rapidly in recent years. Meanwhile, the increase of distributed energy resources brings EI more prone to stability problem. Therefore, the real time state estimation becomes an important aspect to ensure the safe and stable operation of EI.

In the practical power system, the real-time monitoring data usually comes from supervisory data acquisition system (SCADA), which mainly includes active power, reactive power, voltages amplitude and so on. The interval of data acquisition is second level, and the real-time and accuracy of voltage phase angles are poor due to the error during the data transmission process. Therefore, the transient process during faults and disturbances cannot be monitored only through SCADA.

With the emergence and development of phase measurement unit (PMU), the synchronous phase can be measured in real time using GPS for timing. PMU transmits data quickly and has phase angle measuring device, which ensures the real-time of the data acquisition. Meanwhile, with the sampling rate higher than 100Hz, PMU is able to collect the transient data during faults [1]. Based on PMU data, many applications have been proposed, such as event detection [2] and fault diagnosis [3]. However, compared with SCADA, the high cost and difficult maintenance make it difficult to guarantee the installation of PMU measurement on every bus [4]. Therefore, the fusion of the data from limited PMUs and SCADA for state estimation has been a major research subject in recent years.

With the rapid development of artificial intelligence in recent years, artificial intelligence has been applied to many subjects in EI, such as reactive power consumption [5], energy management [6] and renewable energy storage [7]. To achieve the state estimation of power system, some data-driven methods have been proposed [8], [9]. However, the aforementioned methods that only combine monitoring data as artificial intelligence input are totally data-driven. The topology that serves as domain knowledge of EI has not been considered properly, which results in the poor robustness of deep learning methods, especially under variable power generations in EI. The EI topology can indicate the interconnection between buses and further facilitate the precise state estimation of EI. With the topology, the monitoring data of EI can be regarded as data with graph structure. Motivated by applying convolutional neural networks (CNN) to data with graph structure, graph convolutional networks (GCN) is proposed by defining convolution operations on a graph [10] with the adjacency matrix, and has been successfully applied in many fields such as traffic prediction [11] and virtual network embedding [12].

Therefore, to fully utilize the multi-source monitoring data and domain knowledge of EI, GCN is introduced to the state estimation of EI during transient process in this paper, and a novel GCN-based state estimation method is proposed for EI using SCADA and PMU data. With the EI topology represented by the adjacent matrix, the multi-source monitoring data

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of each EI bus and its adjacent buses are extracted and fused by the graph convolution operation in GCN. Then the transient states of all EI buses are obtained by the multiple output of GCN. The main contributions of this paper are summarized as follows:

1) GCN is first introduced to state estimation of EI in this paper. By considering EI topology, GCN achieves the fusion of SCADA and PMU data with the adjacency matrix and graph convolution operations.
2) Multiple output batches are constructed in GCN. Thus, transient states of all EI buses can be obtained simultaneously.
3) The case study on an IEEE 9 bus system shows that the proposed method achieves fast transient state estimation and more accuracy transient voltages during faults than the state-of-the-art methods.

The rest of the paper is organized as follows. Section II presents the basic principles of GCN and its advance edition for state estimation. Section III introduces the proposed transient state estimation method for EI. Section IV verifies the proposed method on the simulation of an IEEE 9 bus system. Section V concludes the paper.

II. Graph Convolutional Networks for State Estimation

A. Graph Convolutional Networks

In recent years, CNN has been successfully applied in many fields, since it has strong feature extraction ability on data in array form [13], [14]. Meanwhile, the system with graph structure are more common in our daily life, such as Internet, social network and power grid, the topology of which is significant for the feature exaction and state estimation of these systems.

To apply convolution operation in CNN on data with graph structure, GCN is proposed by deriving graph convolution operation with the adjacency matrix of the graph [15]. GCN is composed of several graph convolutional layers. Considering an undirected graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$ with N nodes $v_i \in \mathcal{V}$, K edges $(v_i, v_j) \in \mathcal{E}$. An adjacency matrix $A \in \mathbb{R}^{N\times N}$ is constructed to indicate the topology, and a degree matrix $D_{ii} = \sum_j A_{i,j}$ is constructed to indicate the degree of nodes. Then a normalized Laplacian matrix L of the graph is obtained by combining A and D [16]:

$$L = D^{-\frac{1}{2}}(D - A)D^{-\frac{1}{2}} = U\Lambda U^T \tag{1}$$

where Λ is the matrix of eigenvalues, U is the matrix of eigenvectors, and ^{T} is matrix transposition operation. Then graph convolution operation is defined by:

$$y = \sigma\big(g_\theta(L)x\big) = \sigma\Big(Ug_\theta(\Lambda)U^T x\Big) \tag{2}$$

where y is the output features of nodes, g_θ is the graph convolutional kernels. $g_\theta(\Lambda)$ represents the graph convolution operation on Λ. x are the input features of nodes, $\sigma(\cdot)$ is the activation function.

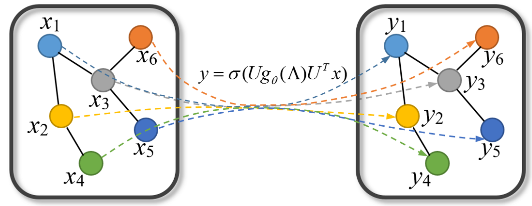


Fig. 1: Structure of a graph convolutional layer.

As shown in Fig. 1, a graph convolutional layer fuses the features of graph nodes with adjacency matrix to obtain the extracted features of nodes. x_i and y_i are the input and output features of the ith node, respectively.

Furthermore, to fuse the node feature and the features of adjacent nodes with a larger distance, a Chebyshev polynomial is operated on Λ by [16]:

$$g_\theta(\Lambda) = \sum_0^{k-1} \beta_k T_k(\tilde{\Lambda}) \tag{3}$$

where $T_k(\cdot)$ is a Chebyshev polynomial of order k, β_k is the convolutional kernels for features in k-th order, $\tilde{\Lambda} = 2\Lambda/\lambda_{max} - I$ is the rescaled Λ to $[-1, 1]$. λ_{max} is the maximum of Λ, and I is the identity matrix. Therefore, the final formula of a graph convolutional layer is defined by:

$$y = \sigma\Big(U \sum_0^{k-1} \beta_k T_k(\tilde{\Lambda}) U^T x\Big) \tag{4}$$

In a graph convolutional layer, features of nodes in different distance of a node are extracted and summed to obtain the output feature of the node. Then several graph convolutional layers can be put in sequence to construct GCN.

B. Graph Convolutional Networks for State Estimation of EI

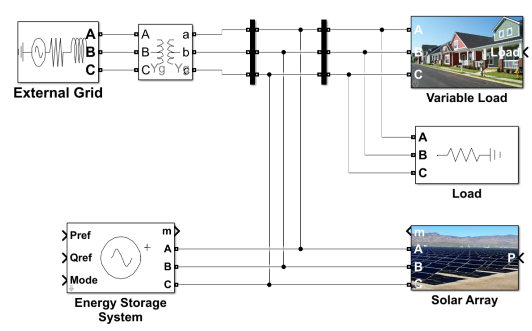


Fig. 2: Structure of a local microgrid in EI.

As shown in Fig. 2, with the power lines connecting buses, EI system is in a typical graph structure. The power flow on power lines indicate the connections between buses, and affects the operation state of EI. Therefore, the consideration of the relationship between the states of nodes is very important for the state estimation of EI. In face of the limited PMU installation, GCN that can explore the potential connection between the data of nodes is a natural choice for EI state estimation based on the correspondence between graph nodes and EI buses.

To make full use of the SCADA data and limited PMU data, the multi-source data should be combined as the input of GCN. The SCADA data is used as the input of nodes without PMU, and the real-time PMU data is used as input of nodes with PMU. Then with SCADA data as initial values, the states of nodes without PMU can be updated by fusing with data of adjacent nodes through the graph convolution operation in GCN.

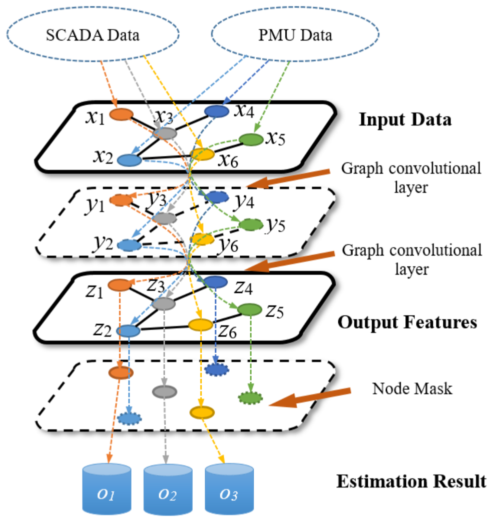


Fig. 3: Structure of GCN for state estimation.

Meanwhile, to obtain the state of nodes without PMU measurement, multiple batches are constructed to generate multiple outputs. As shown in Fig. 3, a mask layer is added after the last graph convolutional layer to indicate the nodes without PMU measurement. Then multiple regression outputs are constructed, and the loss function during the training process is defined as follows:

$$Loss = \sum_{i}^{s} \sum_{j}^{c} (l_{i,j} - o_{i,j})^2 \tag{5}$$

where s is the number of nodes without PMU measurement, c is the number of data channel, $l_{i,j}$ and $o_{i,j}$ are the true value and output value for the j-th data channel of the i-th node.

III. The Proposed State Estimation Method for EI

With the increase of distributed energy resources connected to EI, transient fluctuations often occurs, which affects power quality. It is necessary to monitor the fluctuation of each bus in the transient process. However, the insufficient installation of PMU makes it difficult to obtain transient information of all buses. To solve the problem, based on GCN that can discover the relationship between EI buses, a novel state estimation method is proposed using SCADA and PMU data. Fig. 4 shows the flow chart of the proposed method, the detail steps of which are described as follows:

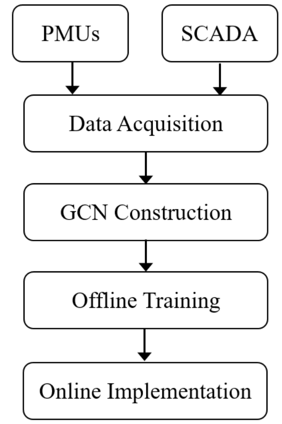


Fig. 4: Flow chart of the proposed state estimation method for EI.

1) Acquisition of EI Monitoring Data: Obtain SCADA monitoring data of buses without PMU and real-time PMU data in high sampling frequency of buses with PMU measurement, which consist of active power, reactive power, frequency and three-phase voltages. Then the state of EI system $S \in \mathbb{R}^{N\times 6}$ is constructed by combining the SCADA and PMU data. N is the number of EI buses. During the transient process, the PMU data in S changes in real-time and SCADA data remains unchanged.

2) Construction of GCN for State Estimation of EI: Construct the GCN model for state estimation according to the topology of EI. The adjacency matrix of corresponding graph structure is established based on the connection of power lines between buses. Then, considering the size of the EI, the structure parameters of GCN are set, and the input and output forms are defined according to the position of PMU nodes.

3) Offline Training of State Estimation Model: Select the data during the transient process of EI with faults and disturbances, Taking state of EI system S as input, and the transient data of non-configured PMU buses as output, the constructed GCN model for state estimation is trained.

4) Online Implementation for Real-time State Estimation: Implement the trained state estimation model of EI buses based on GCN online. Obtain the real-time state estimation results of all EI buses with the input of the SCADA data of all buses and real-time PMU data of some buses obtained online.

IV. Case Study and Result Analysis

To verify the effectiveness of the proposed method, a case study based on an IEEE 9 bus system [17] is carried out in this section.

A. Simulation of EI system

Based on the IEEE 9 bus system shown in Fig. 5, the simulation model of the EI system is constructed using PSD/BPA software. The EI system operates at 230 kV, 50 Hz. Gen 1, Gen 2 and Gen 3 are three generators. Bus A, bus B, bus C

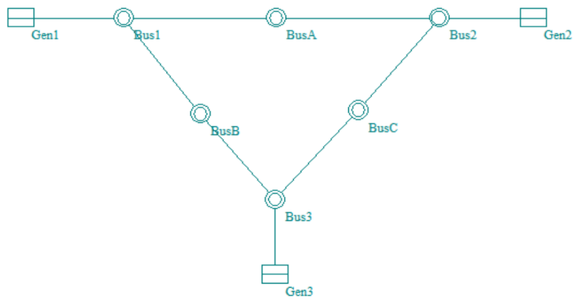


Fig. 5: EI based on the IEEE 9 bus system.

and bus 2 are buses with ZIP loads with different factors. Bus A, bus B, bus C and Gen 2 are mounted with PMUs.

Disturbances and faults are injected using PSD/BPA software to simulate the transient processes in EI system. Disturbances include sudden increase of load on nodes. Faults include one-phase ground, two-phase short circuit, two-phase ground and three-phase short circuit on the power lines between buses. There are 180 transient processes in faults and disturbances conditions totally. Fig. 6 shows the voltage curves of EI nodes when a two-phase ground on phase B and phase C of the power line between bus A and bus 2. The fault occurs at 0.01 seconds, and the protection device actions at 0.02 seconds.

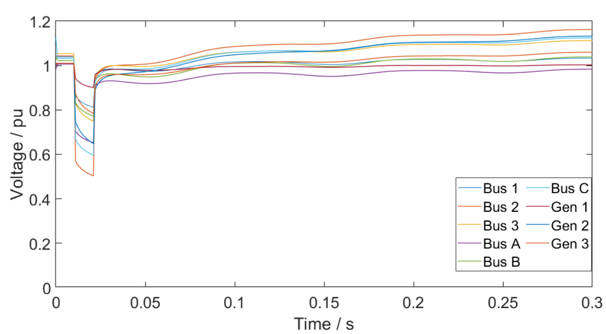


Fig. 6: Voltage curves of buses during a two-phase ground fault.

B. Parameter Setup and Offline Training

To construct the GCN model for the specific EI system, firstly, the graph of EI system is built by taking EI buses as graph nodes and taking power lines in EI as edges of graph. Then, an adjacency matrix with the size of 6×6 is built to describe the EI topology. The GCN model is structured with three graph convolutional layers, and two fully connected layers are followed to extract the features of each node. The detail parameters of the GCN model are list in Table I. The features of the last graph convolutional layer are masked to output of the five buses without PMU measurement. Voltage, frequency and active power are the three channels to be estimated.

With the sampling rate of 100Hz, PMU data of 0.3 seconds, which contains 300 samples, is selected for training. Totally,

TABLE I: Parameters of GCN for State Estimation

No.	Layer Type	Input Size	Parameters	Output Size
1	Graph Convolutional layer	9×6	$6 \times 10 \times 3$	9×10
2	Graph Convolutional layer	9×10	$10 \times 10 \times 3$	9×10
3	Graph Convolutional layer	9×10	$10 \times 5 \times 3$	9×5
4	Mask layer	9×5	9×1	5×5
5	Fully connected layer	5×5	5×10 / 5	5×10
6	Fully connected layer	5×10	10×3 / 5	5×3

42000 samples are used in the offline training, while 12000 samples are used to evaluate the trained GCN state estimation model. The training of GCN model is processed by Tensorflow in Python environment on a computer with a GTX 1070 GPU and 16 GB memory. The learning rate is set as 0.001. During about 290 minutes, the training of GCN model achieves convergence after 5000 epochs. The loss curves for three channels during the training process are shown in Fig. 7, which is relatively stable. The training speed of GCN is slower than CNN, since it GCN the topology of graph and has strong robustness.

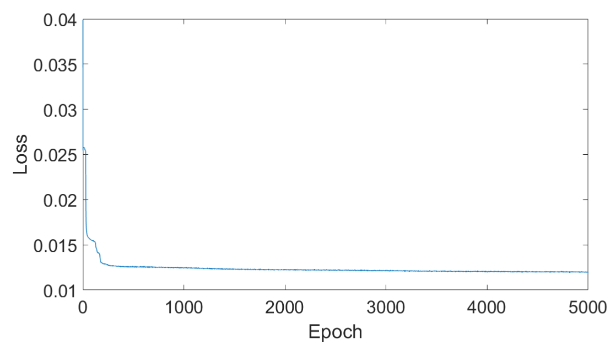


Fig. 7: Loss curves during the training process.

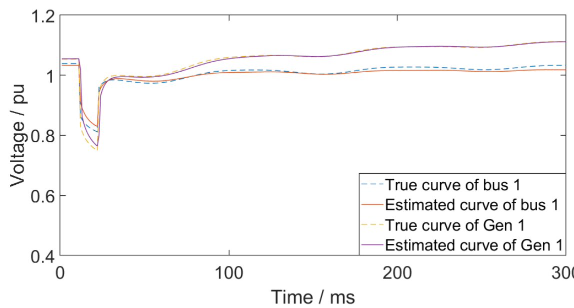
C. Results and Analysis

The average root mean square errors (RSMEs) of the training and test Set for the 3 estimated channels are listed Table II. It can be seen that all the RSME of the voltage, frequency and active power are small compared to the true values, which shows the effectiveness of the method in state estimation.

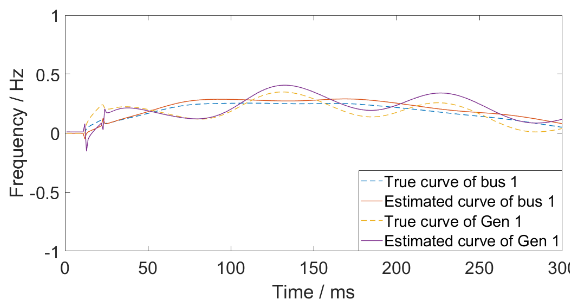
TABLE II: Average RSMEs of Training and Test Set for 3 Estimated Channels

Data Set	Voltage (pu) RSME	Frequency (Hz) RSME	Active Power (MW) RSME
Training	0.058	0.273	1.954
Test	0.073	0.439	2.495

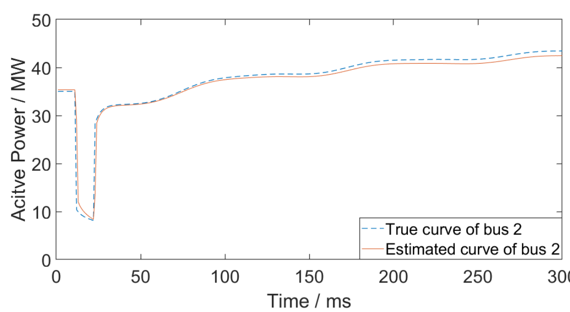
Fig. 8 shows the state estimation result of bus 1 and Gen 1 during the transient process in Fig. 6. It can be seen that the proposed method can obtain accurate estimation for the voltages, frequency and active power of bus 1 and Gen 1. The fluctuations in the curve after protection action is well fitted. The estimation error mainly comes from the fault injection process when the impedance of lines changes dramatically. The influence of impedance variations on GCN model is worth further study.



(a) Voltage curves



(b) Frequency curves



(c) Active power curves

Fig. 8: State estimation results.

V. Conclusion

This paper proposed a state estimation method for EI based on GCN using SCADA and PMU data. Considering the topology EI, GCN fuses the multi-source data of EI buses based on the adjacency matrix. Then multiple task batches are constructed to obtain the transient state of EI buses with PMU measurement in real-time. The case study on an EI system shows that the proposed method can achieve real-time state estimation of EI during faults and disturbances. In future work, with natural multi-output structure of GCN, the optimization problems in EI with multi-agents can be solved by considering EI topology.

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