Graph Learning Empowered Situation Awareness in Internet of Energy With Graph Digital Twin

Liyan Sui, Xin Guan, Chen Cui, Haiyang Jiang, Heng Pan, and Tomoaki Ohtsuki, *Senior Member, IEEE*

***Abstract*—Internet of energy (IoE) is one of the most complex industrial systems, and its stable operation is very important. Situation awareness (SA) has been proposed to ensure the stable operation for IoE and making full use of the relationships between components has become the key point for designing an efficient SA model. In this article, graph digital twin (GDT) is proposed by combining digital twin technology with graph theory, to describe the logical relationships between physical entities more accurately in digital space, and then a novel SA model for IoE based on GDT is proposed. In order to make full use of the relationship between nodes, two classifiers based on graph convolution network are designed for fault location and stability prediction. The experimental results show that the proposed SA model can localize the multiple fault components with high accuracy, and can accurately predict the stability of the system.**

***Index Terms*—Digital twin (DT), graph convolutional network (GCN), internet of energy (IoE), situation awareness (SA).**

I. Introduction

DUE to the continuous expansion of power system scale, the increase of system operation complexity, the change of operating environment, the real-time update of massive data and the rapid development of renewable energy, there are many uncertainties in the actual operation in the modern internet of energy. As a result, it is difficult to accurately understand the current status of the system and predict the future status of the system [1].

Situation awareness (SA) is one of the key factors to ensure the stable operation for the internet of energy, because it can enable operators to effectively and timely grasp the system operation status and make judgments on the future status of the system, so effective SA can further ensure the stable operation of the system [2]. M. R. Endsley firstly proposes the model of SA, and divides it into three levels [3]. The first level is perception of the system state, which consists of the key elements and information of the system. In this level, lots of studies focus on the data measurement and collection, such as placement policy of phasor measurement units (PMUs) for resisting the attack and improving condition estimation accuracy and fault observability [4], [5]. The second level is the comprehension of current system operation status with the existing data, revealing why the system presents a certain status, such as fault location of distribution network based on secondary voltage measurement of low voltage transformer [6], and transient stability assessment using dynamic equivalents and nonlinear observers for large-scale power system in real time [7]. The last level is the prediction of system future state based on the comprehension of current system operation status, so that to timely take effective measures to ensure the stability of system operation. Except the above traditional methods to implement the three-level SA, methods based on machine learning are gradually adopted for realizing SA in internet of energy.

With the development of artificial intelligence technology, some machine learning based methods have been proposed for SA in internet of energy, such as fault location [8], and stability assessment [9]. Considering that the monitored data of power system in real time is incomplete, a generative adversarial network based method is proposed to solve the problem of dynamic security assessment [10]. In order to make better use of the timing characteristics of power system data, long short-term memory (LSTM) network is adopted to identify the power fluctuations in real time [11]. However, there are few studies that consider both the system stability prediction and the fault location, which locate not only buses but also generators. In paper [12], an aggregated model with convolutional neural network (CNN) and LSTM is proposed to realize the system

Manuscript received 1 July 2022; revised 10 October 2022; accepted 13 November 2022. Date of publication 8 December 2022; date of current version 4 May 2023. This work was supported by Management and Consulting Projects of State Grid Corporation of China under Grant SGHL0000DKJS2101201 and in part by the Special Funds of Heilongjiang University of the Fundamental Research Funds for the Heilongjiang Province under Grant 2021-FYYWF-0015. Paper no. TII-22-2886. *(Corresponding authors: Xin Guan; Chen Cui.)*

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Color versions of one or more figures in this article are available at https://doi.org/10.1109/TII.2022.3227641.

Digital Object Identifier 10.1109/TII.2022.3227641

stability prediction and fault location at the same time. However, this model can only realize the fault location of bus without considering the problem of generator fault location, and the influence of the topology of the energy internet on the system characteristics.

As an emerging technology, digital twin (DT) has been exploited for SA in the internet of energy, such as fault diagnosis in distributed photovoltaic systems [13]. The concept of DT is proposed by NASA, and it can represent the physical world in the digital space, diagnosing and maintaining the system based on the processing and analysis of historical data and real-time data [14]. DT has been widely used in the Internet of Things, such as system management based on virtual model [15], monitoring and analyzing the global wind farms [16], making more inverters used to feed renewable energy [17] and the online analysis in real time for the power gird [18]. However, the existing methods of realizing SA for internet of energy based on DT technology do not consider how to realize the relationship representation of physical entities in the digital space. In fact, we can more accurately construct a complete mapping for internet of energy in the digital space by combining the attributes of physical entities with the relationship between entities, so as to better understand the current state of the system and predict the future state of the system. In this article, a method based on graph theory to construct the DT of physical world in virtual space is presented. Then, we design a SAs model based on graph convolutional network to realize fault location and stability prediction for the internet of energy. The main contribution of this article are summarized as follows.

1) We propose a graph theory based method to represent the physical entity in the digital world. Our proposed graph based DT method guarantees the accuracy and completeness of the digital entity significantly. In our proposed graph DT model, we define the physical entity as the node and the relationship between entities as the edge, the generated data of physical world is mapped into the graph. In this way, the graph digital twin (GDT) with complete information of the physical world is constructed in the digital world.

2) Based on graph convolutional network (GCN), we design two classifiers to deeply analyze and process the graph structured data for the SA model. The first classifier is whole graph oriented and it is used for stability prediction, the second classifier is node oriented and it is used for fault location in internet of energy.

3) By using our proposed two well-designed GCN based classifiers within the GDT framework, our proposed SA model can be applied to all the real physical scenarios of stability prediction and fault location in the internet of energy. Therefore, the proposed SA model offers strong practical significance. Furthermore, our proposed SA model can localize the multiple fault components with high accuracy in internet of energy.

The rest of this article is organized as follows. In Section II, we overview the related works. Section III introduces the method based on graph theory to establish virtual representation of physical world in GDT. The situation awareness model based on GCN is presented in Section IV. Section V is the case study that shows the performance of the proposed SA model for internet of energy. Finally, Section VI concludes this article.

II. Related Works

A. Situation Awareness

As one of the earliest definitions of SA, it is described as perceiving the element information in the environment in a certain time and space, understanding its meaning, and predicting its state in the future [3]. SA is becoming increasingly important in many areas involving human decision-making and operations in complex and changeable situations. Therefore, SA is receiving increasing attention in the complex and changeable internet of energy (IoE). In [4], they design optimal PMUs placement policies to reduce the cost of PMUs placement and resist to data integrity attacks. In [19], the method for recovering missing data from PMUs is proposed, which is based on tensor decomposition. In [6], they use the nearest neighbor clustering algorithm to group the measured voltages at different locations to distinguish the upstream and downstream, and use the measured values of the downstream instruments to iteratively search in the predicted fault section to estimate the fault location.

B. Machine Learning

For IoE, the operating principles of components are complex and changeable, and the logical relationships between components are relatively complex. Therefore, it is difficult for the traditional method to accurately realize SA for IoE. In order to accurately reflect the operation state of IoE, machine learning is a relatively effective method. In [20], they construct a warning framework for transmission network security posture, and this framework is designed with power flow model and LSTM model. Moreover, they use ADASYN oversampling to solve the problem of sample balancing. In [21], recurrent neural network is used to train time series data to realize the prediction and evaluation of generator oscillation stable state. In [12], a SA model is proposed based on CNN and LSTM, mining temporal and spatial characteristics of PMUs data simultaneously. This SA model consists of two components, one is the emergency locator for detecting the current fault location and the other is the stability predictor for predicting the future system stability state.

C. Digital Twin

With the support of historical data of sensors, real-time data of sensors and physical model, DT can realizing virtual mapping of physical world in digital space [22]. As a result, DT can enable real-time situational awareness for the physical world by analyzing it in digital space. In [23], they combine DT networks with edge networks to fill the gap between physical edge networks and digital systems. In [17], parameter estimation and system identification are used to build a DT model for inverter to make more suitable inverters for renewable energy in distribution grids. In [18], they use DT for real-time online analysis, reducing the overall time of online analysis and making the online analysis applications have second-level response capabilities.

However, the method of mapping the components and relationships from the Internet of energy to the digital space in the form of graph structure to solve SA has not been considered.

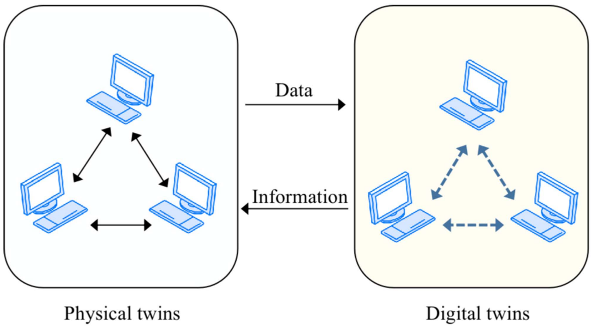

Fig. 1. Model of digital twin.

III. Graph DT

DT is a new technology which combines the physical world with the digital space, using the data generated from the physical world to realize the virtual representation of the physical world in the virtual space. Based on the analysis of the massive data generated from the physical world, the feedback of the state information and control information of the physical world can be realized [23]. The value of DT lies in online accurate monitoring, prediction, simulation, and making decision of physical word [24]. As shown in Fig. 1, the physical objects are mapped to form DTs in the digital space, and DTs can feed back the useful control information to the physical world. DT is mainly composed of the physical world and the digital space. The physical world can be divided into two parts, the physical entities and the logical relationships between them. We define the physical world as $P = (H, R)$, where $H = \{h_1, h_2, \ldots, h_n\}$ and $R = \{r_1, r_2, \ldots, r_n\}$ are the physical entities and the logical relationship between them respectively. In order to better describe the physical world in the digital space, we need to construct a structured virtual representation of the physical world in the digital space. As we known, graph can be used to describe the attributes of object and the relationships between objects. A graph consists of a node set and an edge set. It is defined as $G = (V, E)$, where $V(G)$ is the finite nonempty node set in the graph used to represent objects, and $E(G)$ is the edge set between nodes in the graph, representing the relationship between two objects. In a graph, the relationship between nodes can be arbitrary, and any two elements in the graph can be directly related. Therefore, when there is a strong logical relationship between physical entities, the virtual representation based on graph structure can clearly express the relationship between entities in the digital space, which we call graph digital twin (GDT). The meanings of symbols in GDT are shown in Table I. In this article, the virtual representation of physical entities in the digital world can be defined as $GDT = (V_G, E_G, W, K)$, where the node set $V_G = \{v_1, v_2, \ldots, v_n\}$ represents the physical entities H, a physical entity h_i can be represented by a node v_i in the graph. $E_G = \{e_1, e_2, \ldots, e_n\}$ is the edge set, which is used to represent the logical relationship between any two physical entities. $W = \{w_1, w_2, \ldots, w_n\}$ is the weight set of nodes, which represents the strength of the logical relationship. The edge set and the weight set are used to represent the logical relationship R between physical entities. $K = \{k_1, k_2, \ldots, k_n\}$ indicates the attribute types corresponding to different nodes. By

TABLE I
Symbols for Graph DT

Symbol	Meaning
P	Physical twin
H	The set of physical entities
h_i	A physical entity
R	The set of logical relationships between physical entities
r_i	A logical relationship between physical entities
GDT	Graph digital twin in the digital space
V_G	The set of nodes mapped by the physical entities
v_i	A node mapped by the a physical entity
E_G	The set of edges mapped by the logical relationships
e_i	A edge mapped by a logical relationship
W	The weight set of nodes in GDT
w_i	A node weight in GDT
K	The attribute types corresponding to different nodes
$v_i(t)$	The node i at time t
$s_i(t)$	The state of node $i$at time t
Δd_i	The change for the state of node i
M_i	The node i behavior model obtained through the analysis of historical data
$s_i^{nb}(t)$	The neighbor state of the node i
G_{en}	The set of generators in IoE
B	The set of buses in IoE
T	The set of transmission lines in IoE
P_{en}	The physical twin for IoE
GDT_{en}	The graph digital twin for IoE
V_{en}	The set of the nodes mapped by generators and buses
v_{gi}	The node i of generator
v_{bi}	The node i of bus
E_{en}	The set of edges mapped by the state of transmission lines
K_{en}	The attribute types of different component nodes
k_{gi}	The attribute type on the node of generator i
k_{bi}	The attribute type on the node of bus i

collecting and processing the data of physical entities, a GDT can present the historical and current state of the physical world in the digital form. Therefore, the virtual representation of the node i at tth time can be denoted as

$$v_i(t) = \{s_i(t), \Delta d_i, M_i, s_i^{nb}(t)\} \quad (1)$$

where $s_i(t)$ represents the state of the node i at tth time, Δd_i represents the change for the state of node i, M_i is the behavior model of node i obtained through the analysis of historical data, and $s_i^{nb}(t)$ represents the neighbor state of the node i at tth time. GDT can use the data obtained from the physical world to make a graph structured virtual representation in the digital world, which can clearly and accurately reflect the relationship between physical entities.

DT can be used to monitor and update the status of components in internet of energy in real time. At the same time, through the analysis of the monitored state, the prediction analysis of the internet of energy operation state and the fault location analysis can be realized. Considering that the topology of the internet of energy will also have an impact on the operating characteristics of the system, GDT can better reflect the logical relationship between the components in the internet of energy in the virtual space, so as to evaluate the state of the internet of energy more accurately. The GDT for the internet of energy consists of three parts: physical entity layer, data collection layer and graph digital twin layer as shown in Fig. 2. In the physical entity layer, we use $G_{en} = \{g_1, g_2, \ldots, g_n\}$, $T = \{t_1, t_2, \ldots, t_l\}$, and $B = \{b_1, b_2, \ldots, b_m\}$ to express the sets of generators, transmission lines, and buses, respectively, where n, l, m are the number of generators, transmission lines, and buses, respectively. As mentioned above, G_{en} and B can be regarded as a set of physical entities H, and T can be regarded as a set of logical relationships

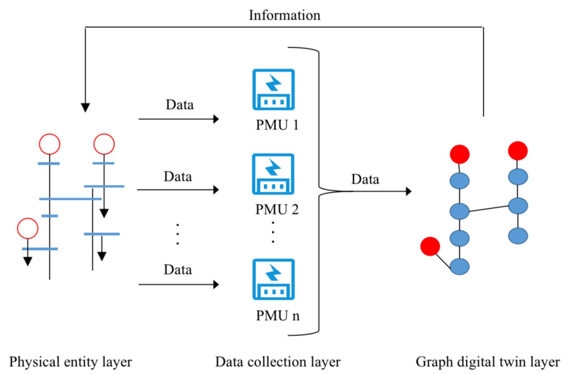

Fig. 2. Graph Digital Twin for the internet of energy.

between physical entities R. So that, the physical twin of the internet of energy is represented as $P_{en} = (< G_{en}, B >, T)$. The data collection layer is the connection between physical world and digital world, which achieves collecting the status of each component in the physical entity layer by using phasor measurement units (PMUs) to collect data of each internet of energy component. The GDT layer collects data from the data collection layer, and finally completes the graph structured virtual representation of the physical world in the digital world.

In the digital world, the graph structured virtual representation of the internet of energy can be represented as $GDT_{en} = (V_{en}, E_{en}, K_{en})$, where $V_{en} = \{v_{g1}, \ldots, v_{gn}, v_{b1}, \ldots, v_{bn}\}$ represents the set of generators and buses, v_{gi} is the node of generator, v_{bi} is the node of bus, and $E_{en} = \{e_{r1}, e_{r2}, \ldots, e_{rn}\}$ indicates the status of transmission lines between different component nodes. Since this article does not consider the importance of nodes and edges in the internet of energy, we do not set the weights of nodes or edges. $K_{en} = \{k_{g1}, \ldots, k_{gn}, k_{b1}, \ldots, k_{bn}\}$ represents the attribute types of different component nodes, where k_{gi} is the attribute type on the node of generators and k_{bi} is the attribute type on the node of buses.

In the internet of energy, the virtual representation of any node at the tth time nodes can be denoted as (1), where $s_i(t)$ is the current state of the buses and generators, Δd_i is the data changes of the internet of energy state, M_i is the node behavior model obtained through the analysis of historical data, and $s_i^{nb}(t)$ is the state of the adjacent elements. Changes in internet of energy components will lead to corresponding changes in GDT. By analyzing the structured data in GDT, the state changes of internet of energy can be predicted, and the faulty components in the internet of energy can be found in time, so as to form control information and feed back to the internet of energy.

In order to realize the SA of the internet of energy, GDT first structurally processes the data, and uses the structured data to predict the future internet of energy status. Then, GDT feeds back the predicted information to the internet of energy so that the internet of energy can deal with incidents accordingly.

IV. Situation Awareness

A. SA Model With GDT

According to the define for SA, it can be divided into three levels: 1) perception; 2) understanding, 3) prediction [25]. Here,

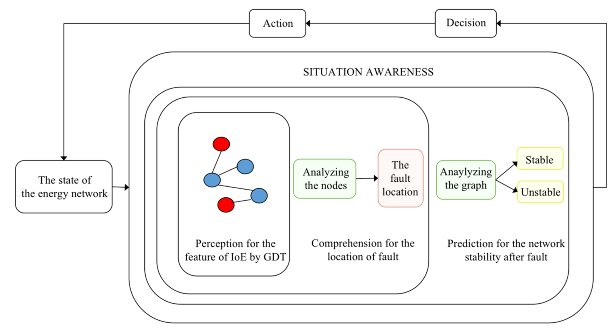

Fig. 3. SA for the internet of energy based on the GDT.

Algorithm 1: Steps of Situation Awareness for IoE.

Input: The physical twin of the internet of energy $P_{en} = (< G_{en}, B >, T)$;
Output: The results of stability prediction and fault location;

Perception for the feature of IoE and constructing the GDT model $GDT_{en} = (V_{en}, E_{en}, K_{en})$;
Outputting the graph-structured data Z and adjacency matrix A;
Initializing $i = 0$, $j = 0$, I represents the train epoch of GCN for the fault location, J represents the train epoch of GCN for the stability prediction;
while $i <= I$ **do**
  Training the classifier for fault location by (13);
end while
while $j <= J$ **do**
  Training the classifier for stability prediction by (15);
end while
while fault happen **do**
  Inputting A and Z to the classifier for fault location;
  Inputting A and Z to the classifier for stability prediction;
end while
return The results of stability prediction and fault location.

we can combine the above three-layer SA model with the internet of energy to obtain a new GDT based internet of energy SA model, as shown in Fig. 3. Firstly, GDT processes and analyzes the data generated by the internet of energy. Then, we classify each structured component node information to achieve fault location in the internet of energy, and the structured data to achieve the prediction of the internet of energy stability. After completing the above three-layer SA, the adjustment strategy of the internet of energy can be obtained, and the internet of energy can be adjusted according to the fault location, and the stability prediction. The steps of SA for IoE is shown in Algorithm 1.

In this article, we first use the physical information of the internet of energy to make a virtual mapping in GDT, using the collected physical data of the internet of energy to make a graph structured representation, so as to obtain the graph structured data including the attribute states of the component nodes and the adjacency matrix. The analysis of graph based structured data can usually be divided into two types, one is node-focused problem and the other is graph-focused problem. The node-focused problem depends on the node information, and the implementation of classifiers or regressors depends on the attribute of each node. The graph-focused problem is independent of the nodes and implements a classifier or a regressor on graph structured data sets [26]. Therefore, we regard internet of energy fault location and stability prediction in SA as classification problems. The fault location of internet of energy is the node classification problem, and the stability prediction of internet of energy is the whole graph classification problem. The fault location can be regarded as a multiple classification problem. The nonfault bus node is labeled as [0,0], the fault bus node is labeled as [0,1], the nonfault generator node is labeled as [1,0], and the fault generator node is labeled as [1,1]. Stability prediction can be regarded as a binary classification problem, so a label information can be set for each graph, labeling the stable graph of internet of energy as 0 and the unstable graph as 1.

B. Graph Neural Network

Although some existing machine learning SA models can locate faults and predict system stability, they cannot directly process graph data well. Since the proposed model implements the SA of system by analyzing the graph structured data in GDT, GNN is adopted to design the SA model. As an extension of neural network, GNN can directly convert the graph data into the output of the graph learning architecture without any processing. Therefore, the GNN based SA model can process graphic structure data efficiently and accurately, so as to implement the SA for internet of energy [27].

The goal of GNN is to learn the hidden state n_v of nodes. Each node obtains the information from the other neighbors, and updates the hidden state with these information. n_v can be used to generate the output l_v, such as labels [28]. n_v and l_v are defined as

$$n_v = f\left(z_v, z_{co[v]}, n_{ne[v]}, z_{ne[v]}\right) \tag{2}$$

$$l_v = g(n_v, z_v) \tag{3}$$

where f is the local transition function that updates the state of node based on inputting. g is the local output function, which describes the way of generating the output. z_v and $z_{co[v]}$ are the features of v and edges to which v is connected. $n_{ne[v]}$ is the state information of v, and $z_{ne[v]}$ are the features of its neighborhoods. According to Banach's fixed point theorem [29], the iteration for computing the state can be described as

$$N^{t+1} = F(N^t, Z) \tag{4}$$

where N^t is the state after t iterations, X is the vector constructed by stacking all the features and F is the global transition function.

The efficiency of the original GNN model is relatively low when updating the status of fixed points, and the performance of the original GNN for node classification is not very satisfactory. In order to accurately describe the status of nodes and the relationship between nodes in internet of energy, the collected data by PMUs is graph structured in GDT, and we need to process not only the information of whole graph but also the information of node, so the original GNN is not suitable for the SA model proposed in this article. Therefore, the SA model proposed is designed based on GCN, which can better classify graphs and nodes by introducing convolutional operations and using effective transmission rules.

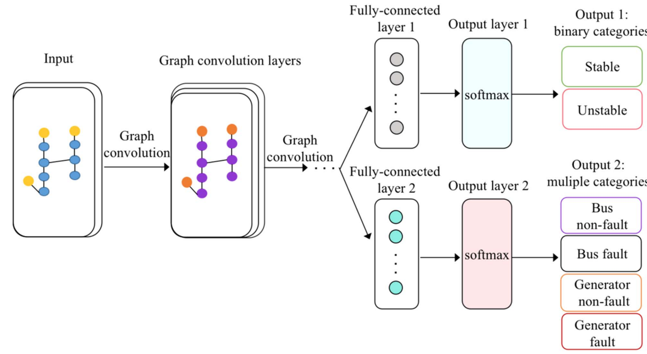

Fig. 4. Framework of SA model based on GCN.

C. Graph Convolutional Network for SA

In this article, GCN is adopted to design the SA model for fault location and stability prediction in the internet of energy. The framework of proposed SA model based on GCN is shown in Fig. 4. The framework including input layer, graph convolution layers, fully connected layers, and output layers. There are two kinds of fully connected layers and output layers. One is used to predict stability based on binary classification, the other is used for fault location based on multiple classification. Laplacian matrix is an important matrix to embody the state of the graph. Laplacian matrix is denoted as $\Gamma = D - A$, where D is the degree matrix, and A is the adjacency matrix. The elements of the Laplacian matrix can be defined as

$$\Gamma_{i,j} = \begin{cases} \mathrm{diag}(v_i) & i = j \\ -1 & i \neq j \text{ and } v_i \text{ is adjacent to } v_j \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

where $\mathrm{diag}(v_i)$ is the degree of the ith node. The normalized Laplacian matrix is denoted as $\Gamma^{\mathrm{sym}} = D^{-\frac{1}{2}}\Gamma D^{-\frac{1}{2}} = I - D^{-\frac{1}{2}}AD^{-\frac{1}{2}}$, and its matrix elements can be defined as

$$\Gamma^{\mathrm{sym}}_{i,j} = \begin{cases} 1 & i = j \text{ and } \mathrm{diag}(v_i) \neq 0 \\ -\frac{1}{\sqrt{\mathrm{diag}(v_i)\mathrm{diag}(v_j)}} & i \neq j \text{ and } v_i \text{ is adjacent to } v_j \\ 0 & \text{otherwise.} \end{cases} \tag{6}$$

The laplacian matrix is a semipositive matrix so that $\lambda_{\min} >= 0$, where $\lambda_{\min}$ is the smallest eigenvalue of the matrix. Due to $\Gamma \times I = 0$, there is $\lambda_{\min} = 0$, and the eigenvalue of the normalized Laplacian matrix has an upper bound ($\lambda_{\max} <= 2$), where $\lambda_{\max}$ is the largest eigenvalue.

1) GCN for Fault Location: To locate the fault and predict the stability in the internet of energy, a graph-based neural network model $f(Z, A)$ is needed to process the graph data, where Z represents the features of node reflecting the state information of components in the internet of energy, A is adjacency matrix of the graph denoting the relationship between components. The layer-wise propagation rule of the GCN model can be denoted as [30]

$$N^{(l+1)} = \sigma\left(\widetilde{D}^{-\frac{1}{2}}\widetilde{A}\widetilde{D}^{-\frac{1}{2}}N^{(l)}Q^{(l)}\right) \tag{7}$$

where $\widetilde{A} = A + I$ represents that an identity matrix is added to the the adjacency matrix of the undirected graph. $\widetilde{D} = D + I$, and $\widetilde{D}_{ii} = \sum_j \widetilde{A}_{ij}$. $Q^{(l)}$ is a weight matrix that can be trained. $\sigma(\cdot)$ is an activation function. In this article, *Relu* is selected as the activation function for input layer and hidden layer, and *softmax* is selected as the activation function for output layer. $N^{(l)}$ is the matrix of activations in the lth layer.

The spectral convolutions of graph can be described as applying a filter $d_\delta = \text{diag}(\delta)$ to the signal in the Fourier domain as

$$d_\delta \star z = \Psi d_\delta \Psi^T z \tag{8}$$

where Ψ is the matrix of eigenvectors of the normalized graph Laplacian $\Gamma = I - D^{-\frac{1}{2}}AD^{-\frac{1}{2}} = \Psi\Lambda\Psi^T$, and $\Psi^T z$ is the Fourier transform of z, so that we regard d_δ as a function of the eigenvalues $d_\delta(\lambda)$ of Γ, we can evaluate it by a truncated expansion in terms of Chebyshev polynomials $T_k(x)$

$$d_\delta(\Lambda) = \sum_{k=0}^{K} \delta'_k T_k(\widetilde{\Lambda}) \tag{9}$$

where $\widetilde{\Lambda} = \frac{2}{\lambda_{\max}}\Lambda - I$, $\lambda_{\max}$ is the largest eigenvalues of Γ. δ is a vector of Chebyshev coefficients. Then we put the Chebyshev polynomials recursively definition into (8), we now have

$$d_\delta \star z = \sum_{k=0}^{K} \delta'_k T_k(\widetilde{\Gamma})z \tag{10}$$

where $\widetilde{\Gamma} = \frac{2}{\lambda_{\max}}\Gamma - I$. Kth-order polynomial in the Laplacian, which only depends on its Kth-order neighbor. GCN limits the convolution operation to $K = 1$ in each layer, then make $\lambda_{\max} \approx 2$. For preventing overfitting, the number of operations are minimized, and (10) can simplifies to

$$d_\delta \star z \approx \delta\left(I + D^{-\frac{1}{2}}AD^{-\frac{1}{2}}\right)z \tag{11}$$

Due to $I + D^{-\frac{1}{2}}AD^{-\frac{1}{2}}$ has eigenvalues in the range [0, 2], we can make $I + D^{-\frac{1}{2}}AD^{-\frac{1}{2}} \to \widetilde{D}^{-\frac{1}{2}}\widetilde{A}\widetilde{D}^{-\frac{1}{2}}$ to prevent gradients exploded. When the node in graph is vector, (11) can denote as

$$M = \widetilde{D}^{-\frac{1}{2}}\widetilde{A}\widetilde{D}^{-\frac{1}{2}}Z\Delta. \tag{12}$$

where Δ is a matrix of filter parameters, and M is the convolved signal matrix.

In this article, we regard the fault location as a multiple classification problem, which means the components in the internet of energy should be divided into four categories: 1) fault buses; 2) nonfault buses; fault generators; 4) nonfault generators. The difficulty of classification increases, at the same time the strength of feature extraction should also increases. Therefore, we use a three-layer GCN for nodes classification to locate the fault nodes. We first compute $A_f = \widetilde{D}^{-\frac{1}{2}}\widetilde{A}\widetilde{D}^{-\frac{1}{2}}$, and the feedforward propagation model has the form as follows:

$$\begin{aligned} M_l &= f_l(Z, A) \\ &= softmax\left(A_f ReLU\left(A_f ReLU\left(A_f Z Q_l^{(0)}\right)Q_l^{(1)}\right)Q_l^{(2)}\right) \end{aligned} \tag{13}$$

where $Q_l^{(0)}$ is an input-to-hidden weight matrix, $Q_l^{(1)}$ is a hidden-to-hidden weight matrix, and $Q_l^{(2)}$ is a hidden-to-output weight matrix in the three-layer GCN. Z is the features of the nodes. The features on the nodes of generators and buses are both electron current. We locate the fault including two kinds of nodes, which are mapped by buses and generators.

In this article, we regard the fault location for internet of energy as multiclassification. So the loss function can be written as follow:

$$Loss_l = -\frac{1}{u}\sum_{w=1}^{u}\sum_{a=1}^{s}\sum_{i=1}^{n}[q_{w,a,i}\log(\hat{q_{w,a,i}})] \tag{14}$$

where $Loss_l$ is a multiclassification cross entropy, s is the count of nodes in graph, n is the kinds of nodes. $q_{w,a,i}$ denote the actual probability for the label i of the ath node in the wth example. $\hat{q_{w,a,i}}$ is the possibility for for the label i of the ath node in the wth example.

2) GCN for Stability Prediction: In this article, we use a two-layer GCN for the graph classification to predict the internet of energy stability. Our forward model take the form as follow:

$$\begin{aligned} M_p &= f_p(Z, A) \\ &= softmax\left(\tau\left(A_f ReLU\left(A_f Z Q_p^{(0)}\right)Q_p^{(1)}\right)\right) \end{aligned} \tag{15}$$

where Z is the features of the nodes. Voltage can be selected as the feature of generator node, and electron current can be selected as the feature of bus node. $Q_p^{(0)}$ is an input-to-hidden weight matrix, and $Q_p^{(1)}$ is a hidden-to-output weight matrix in the two-layer GCN. $\tau(\cdot)$ denotes a function that transforms a node vector into a graph vector representing a graph.

The stability prediction is to predict the status of the whole internet of energy, and we regard it as a graph classification problem. The features of nodes and the adjacency matrix of the graph are input into the prediction model, and the representation of the graph can be output to indicate the stability of the system. In this article, we can get the global representation of the graph by mean pooling the features of nodes features, so as to realize the classification of the whole graph.

In this article, we regard the internet of energy stability as binary classification, the loss function can be written as follow:

$$Loss_p = -\frac{1}{u}\sum_{w=1}^{u}[p_w log\hat{p_w} + (1 - p_w)\log(1 - \hat{p_w})] \tag{16}$$

where $Loss_p$ is a binary cross entropy denote the internet of energy stability prediction, where u is the count of examples, p_w the actual probability of the wth example is stable, and $\hat{p_w}$ the possibility of the wth example is stable.

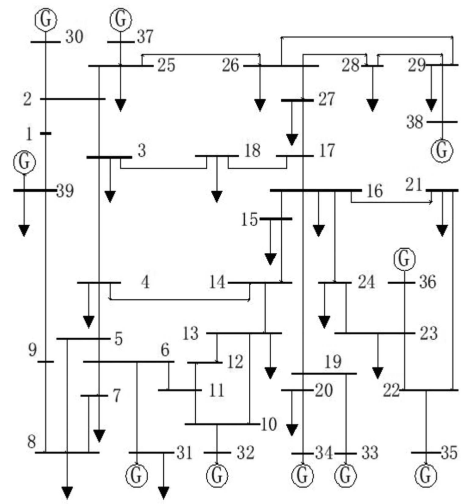

Fig. 5. New England system with 39 buses and 10 generators.

V. Case Study

The proposed SA model based on GDT and GCN is tested on the New England test system with 39 buses and 10 generators as shown in Fig. 5.

A. Performance on Stability Prediction

In order to better verify the dependence of the proposed stability prediction model on the components in the internet of energy, the information of buses and generators are mapped into a graph to predict the stability of system respectively. Fig. 6 shows the training process only with the mapped information of buses. In this training process, the learning rate are set to 0.0001, 0.0003, and 0.0005, respectively. As shown in Fig. 6(a), when the learning rate is 0.0001, the model does not fully reach the convergent state after 5000 iterations. When the learning rate is 0.0003 or 0.0005, the loss decreases significantly with the number of iterations increasing. When the number of iterations reaches to 5000, the loss has reached to a relatively low level, which can indicate that the model is in a convergent state. As Fig. 6(b) shows, the learning accuracy for stability prediction with buses increases with the number of iterations increasing, and it can also increase with the increase of the learning rate. As shown in Fig. 6(b), when the learning rate is set to 0.0005, the learning accuracy achieves a quite ideal result after 5000 iterations. Fig. 7 shows the training process only with the mapped information of generators. In this training process, the learning rate are set to 0.001, 0.003, and 0.005 respectively. As shown in Fig. 7(a), when the learning rate is 0.003, the model can fully reach the convergent state after 100 iterations, however the losses fluctuates greatly after the 45th iteration. When the learning rate is 0.001 or 0.005, the loss decreases significantly after 25 iterations. When the number of iterations reaches to 100, the loss has reached to a relatively low level, which can indicate that the model is in a convergence state. As shown in Fig. 7(b), no matter which of the three learning rates we choose, the learning accuracy can achieve a quite ideal result after 100 iterations. It is clear that the training process can achieve an ideal result with

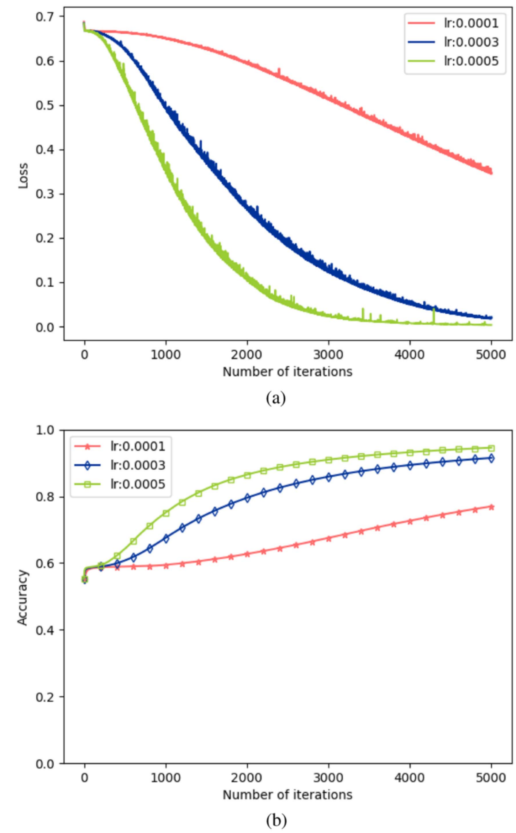

Fig. 6. Performances of stability prediction model using buses. (a) The loss of stability prediction model using buses. (b) The learning accuracy of stability prediction model using buses.

TABLE II
Stability Prediction Performances on Different Test Sets Using Buses

	Test set A	Test set B	Test set C	Test set D
Precision	1.0000	0.9862	0.9990	0.9852
Recall	0.9860	1.0000	1.0000	1.0000
f1-Score	0.9929	0.9931	0.9995	0.9926
Accuracy	0.9922	0.9930	0.9995	0.9925

a reasonable learning rate, no matter what kind of component in internet of energy is chosen for GDT construction.

In order to further evaluate the performance of our proposed stability prediction model, the dataset is divided into four parts, one of which is selected as the test set and the others as the training set each time. In addition, we use precision, recall, F1 score, and accuracy to evaluate the performance of stability prediction. Table II shows the results of stability prediction in four different test sets, only using the information of buses. It can be seen that the accuracy for test set A is relatively low, but over 99%. When the test set is selected as test set C, the accuracy can reach to 99.95%. Table III shows the results of stability prediction in four different test sets, only using the information of generators. It can be seen that the accuracies for test set B and test set C are relatively low, but over 98%. When the test set is selected as Test set D, the accuracy can reach to 99.80%. The performance of stability prediction in different test sets using the information of all elements is shown in Table IV. The accuracy

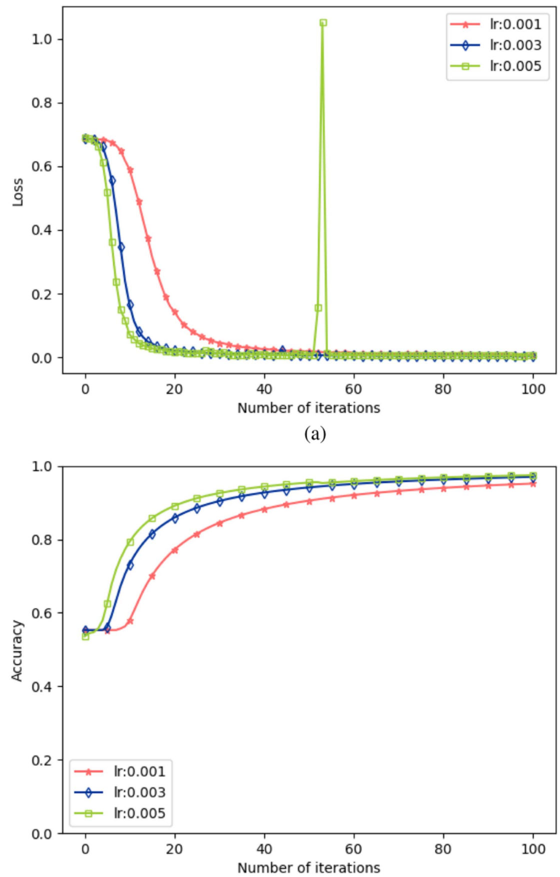

Fig. 7. Performances of stability prediction model using generators. (a) The loss of stability prediction model using generators. (b) The learning accuracy of stability prediction model using generators.

TABLE III
STABILITY PREDICTION PERFORMANCES ON DIFFERENT TEST SETS USING GENERATORS

	Test set A	Test set B	Test set C	Test set D
Precision	1.0000	0.9616	0.9704	0.9960
Recall	0.9900	1.0000	1.0000	1.0000
f1-Score	0.9949	0.9804	0.9850	0.9980
Accuracy	0.9944	0.9800	0.9866	0.9980

TABLE IV
STABILITY PREDICTION PERFORMANCES ON DIFFERENT TEST SETS USING BUSES AND GENERATORS

	Test set A	Test set B	Test set C	Test set D
Precision	0.9814	0.9980	0.9927	0.9860
Precall	1.0000	1.0000	1.0000	1.0000
f1-Score	0.9940	0.9990	0.9963	0.9930
Accuracy	0.9940	0.9990	0.9957	0.9941

on the four test sets are over 99%, and the accuracy on the test set B can reach 99.90%. As shown in Tables II, III, and IV, it is clear that the performances are almost perfect, no matter which kind of components are chosen to predict the stability. As the experimental results show, the proposed stability prediction model can obtain good results with different kinds of components.

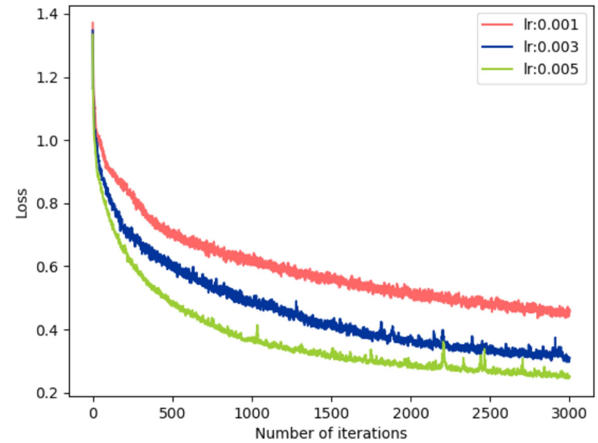

Fig. 8. Loss of fault location model.

TABLE V
MULTIPLE FAULT LOCATION ACCURACY FOR DIFFERENT COMBINATION OF COMPONENTS

	Accuracy		Accuracy
B1+G1	97.50%	B3+B18+G10	96.50%
B4+B6	95.08%	B6+B15+G3	98.25%
B7+B14	97.27%	B13+B19+B26	95.28%
B12+B33	94.78%	B14+B16+B20	97.11%
B16+G7	98.40%	B20+G3+G9	96.62%
B20+B24	95.97%	B21+B33+G5	96.85%
B24+G2	98.92%	B26+B28+B39	97.80%
B28+G6	96.08%	G4+G5+G10	100%

B. Performance on Fault Location

In this article, the fault location of components is considered as a node classification problem. Because we use the New England system to evaluate the performance of proposed fault location model, we divide the types of nodes into four types: fault bus nodes, nonfault bus nodes, fault generator nodes, and nonfault generator nodes. In the proposed fault location model, it is essay to locate the faulty nodes in the system as long as we can classify the types of nodes more accurately. For the fault location test, we use the same data set as stability prediction.

Fig. 8 shows the training process for proposed fault location model. In this training process, the learning rate are set to 0.001, 0.003, and 0.005 respectively. As shown in Fig. 8, when the learning rate is set to either of them, the loss decreases significantly with the number of iterations increasing. When the number of iterations reaches to 3000, the loss has reached to a relatively low level, which can indicate that the model is in a convergent state. In this article, we mainly focus on the location of multiple faulty components. In order to better verify the performance of proposed fault location model, system with two types of fault nodes and system with three types of fault nodes are tested respectively, the results of accuracy for multiple fault location are shown in Table V. It is clear that the accuracies of locating the multiple faulty components are basically greater than 95%.

TABLE VI
STABILITY PREDICTION PERFORMANCES ON LESS MEASUREMENT NUMBER

	1 G	1B	1G+1B	Half G	Half B
Precision	0.9940	0.9579	0.9652	0.9960	0.9978
Recall	1.0000	1.0000	1.0000	1.0000	1.0000
f1-Score	0.9970	0.9785	0.9823	0.9980	0.9989
Accuracy	0.9970	0.9780	0.9820	0.9980	0.9989

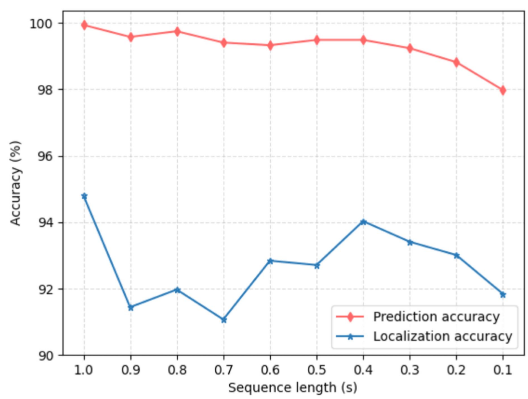

Fig. 9. Performance of SA model with decreasing sequence length.

C. Performance With Inadequate Data

The above results are based on a relatively adequate combination of data. However, the adequacy of data is not always guaranteed in practice. PMUs used for data collection may not be configured to all nodes in the internet of energy so that the data of some components can not be collected. As shown in Table VI, we use different PMUs configurations to collect different number of components for stability prediction, where G represents the generator and B represents the bus. There are five kinds of configurations to realize stability prediction, including one generator, one bus, one generator and one bus, half number of generators, and half number of buses. It is clear that the accuracy of one bus is relatively low but still reaches to 97.80%, and the performance of other configurations is comparable to the performance when using all PMUs. As the experiments shown, the proposed stability prediction model can perform well without being affected by different PMUs configurations.

In practice, SA model may need a faster response speed, by inputting shorter time series data to achieve stability prediction and fault location. To verify the impact of time series data length on proposed SA model, we gradually reduce the length of the input sequence from 1 s to 0.1 s. The performance of SA model with decreasing sequence length is shown in Fig. 9. It is clear that the prediction accuracy decreases with the shortening of the time series data length. However, the accuracy of the stability prediction is still over 98% at 0.1 s. The location accuracy shows a similar but slightly different downward trend. On the global trend, the location accuracy is reduced with the time shorten. The location accuracy of different time lengths fluctuates slightly, which are all above 90%. When the time series length is 0.1 s, the location accuracy can still reach to 92%. Experimental results show that IoE situational awareness with high accuracy can be achieved with 0.1 s of continuous data, even with insufficient time series data.

VI. CONCLUSION

In this article, we firstly propose a graph theory based method to represent the physical entity in the digital world, guaranteeing the accuracy and completeness of the digital entity significantly. In our proposed graph DT model, we define the physical entity as the node and the relationship between entities as the edge, the generated data of physical world is mapped into the graph. In this way, the GDT with complete information of the physical world is constructed in the digital world. Then, we design two classifiers to deeply analyze and process the graph structured data for the SA model based on GCN. The first classifier is node oriented and it is used for fault location, the second classifier is whole graph oriented and it is used for stability prediction in internet of energy. Experimental results show that our proposed SA model can be applied to the real physical scenarios of fault location and stability prediction in the internet of energy. Furthermore, our proposed SA model can localize the multiple fault components with high accuracy in internet of energy.

For future studies, there are still some aspects which should be improved for our proposed GDT framework and SA model. More different logical relationships in IoE should be explored to build the GDT, so that the physical world can be more accurately described in the digital space, improving the performance of situational awareness. At the same time, better methods of feature extraction and representation should be designed to improve the performance of SA model based on GCN. To reduce the cost of PMUs configuration, the method of using fewer components to achieve fault location is also worth studying in the future.

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