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Power Network Topology Identification based on Graph Attention Network

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Abstract:

Identifying and tracking power grid topology changes is a prerequisite requirement for grasping the operating behavior of the power system. The data collected by the power information system can be used to obtain the characteristic quantities describing the state of lines and nodes in the power grid. The traditional classification method ignores the correlation between samples, which affects the identification accuracy. In this paper, we propose a topology identification method based on graph attention network. Firstly, we describe the line features according to the grid information data. Secondly, based on the graph attention network method, we identify line status by line classification. Finally, the power network topology is generated by combining the adjacency matrix and line classification decision to achieve topology identification. IEEE59 node system and an actual provincial power system are tested. The result shows that the proposed method is effective and more accurate in topology identification than traditional methods.

Keywords:*Power networks, Topology identification, Graph attention networks, Data-driven, Graph data, Power grid.*

I. INTRODUCTION

Timing grasping the power network topology changes is a prerequisite for the exceptional management and safe operation of power grids [1]. As the scale of the grid continues to expand, we need to re-maintain the node and branch parameter information when new lines are added to the grid or the network topology changes [2]. Due to the rapid development of China's power grid construction, the workload on information

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system maintenance is enormous. The graphical system is not updated on time, which can lead to errors in the identification of the system topology and subsequent analysis [3].If we can directly generate topology based on measured data, then the above problems can be reasonably solved.

At present, the primary methods on power grid topology identification are methods based on association matrix [4] or adjacency matrix [5], methods based on network topology tracking [6], methods based on object-oriented techniques [7] and methods based on graph theory [8-10], interval-oriented topology analysis [11-14] and topology identification based on immune algorithms. These methods require information about the connection and switching status of the grid components in the topology identification process. In the actual operation of the power grid, the state of the circuit breakers or switches frequently changes, in which there is inevitably miss operation or refuse operation. These conditions will directly affect the topology recognition effect.

In fact, in addition to the switch status information represented by remote signaling data, the power information system also records telemetry data reflecting the system's operating status at all times. These data can be utilized to supplement the remote signaling data to identify the connection status of the line. Thus, we can establish a route for topology identification by integrating telemetry data and remote signaling data to determine the line connection state. Significant differences exist between the number of features due to running or exiting components. Combining the power flow and switching state information of the grid branch, we can identify the topological changes by classifying the multidimensional characteristic quantity.

Traditional classification methods are mostly applied to structured data. Typical graph data, such as topological data, can only be judged by transforming them into grid data. Secondly, traditional methods mostly ignore the correlation between samples and are not capable of making decisions beyond the training set data. It can lead to overfitting when modeling some data that also has specific noise, which can affect the classification results. Besides, the black-box effect makes it almost impossible to control the internal operation of the model. These methods can only attempt between different parameters, and the outcome may vary with different settings. For multiple classification results, it is also necessary to combine the system operation rules for re-judgment and topology identification.

Graph convolutional networks have become one of the hottest approaches in deep learning [15]. Its main application is meant for non-European spatial data. Well known to all, topological data is a kind of graph data. Graph convolutional networks can serve as a suitable means to analyze topological data. Its function is primarily to analyze the nodes and edges by combining the characteristics of the nodes themselves and their neighbors [16]. The main applications include tasks such as node and edge classification, link prediction, and recommendation. The most important thing is how to use the information of neighbor nodes to classify, predict, and recommend node and edge features. As a representative graph convolutional network, the Graph Attention Network (GAT) introduces an attention mechanism to achieve better neighbor aggregation. By learning the weight of neighbors, GAT can make a weighted gathering of neighbors and improve the decision accuracy of different classifications. Therefore, GAT is not only more robust to noisy neighbors, but also the attention mechanism gives the model a certain degree of interpretability, which provides a new approach for power network topology recognition.

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This paper proposes a topological discrimination method based on graph attention networks. Firstly, to construct characteristic quantity reflecting the state of the line based on data such as telecommunication and telemetry. Secondly, training and learning of the above feature quantity based on graph attention networks to generate identification rules. Finally, the line state is identified according to the learned rules, which enable the generation of power network topology and the identification of topology changes.

In this paper, we apply the method in simulated networks and real power grids. The results indicate that this method is feasible. It can accurately identify network topology. There is no need for data transformation. This method allows direct identification of the line state without the need for a second determination.

II. METHODS FOR CONSTRUCTING LINE STATE FEATURE QUANTITIES

2.1Relationships between Telemetry Data, Remote Signaling Data, and Topology

The topology of bus nodes and inter-node connection branches in a power network can be represented by a matrix of connection relations between bus nodes, i.e., the node incidence matrix. If there is a connection between two nodes, the corresponding position element in the node incidence matrix takes 1. Otherwise, it takes 0.

With the continuous development of the power information system, the system records a large number of grid operation data reflecting the operating status of the order. The data that can reflect the state of the line connection exists in it. Correlations between nodes are cause-and-effect with line related telemetry data and remote signaling data. The corresponding element of the correlation matrix is 1 or 0, which directly determines whether the relevant telemetry data and remote signaling data exists or not.

Then, when the node incidence matrix cannot be obtained directly, we can directly infer the value of the corresponding position element in the association matrix according to the relevant telemetry data and remote signaling data. For example, the remote signaling data directly reflect the amount of state of the double-ended switch of the line. Aremote signaling data of zeroindicates that the line is disconnected when the remote signaling data is zero. When telemetry data is not "null," it suggests that the line is in operation. Moreover, when the telemetry data is zero, it means the line is out of service, in probability. This property described above contributes to the identification of the network topology.

2.2Methods for Constructing Line Feature Quantities

A fixed field describes the attribution of each line in the power information system. For example, "Station A.L Line", "Station B.L Line". This description shows that the L line is the line that connects node A and node B.Traversing through all the description fields of the line, the affiliation of the line to the node can be clarified. This description provides the necessary information for constructing the node association matrix.

For any of these lines, there is a first and an end.The corresponding data add up to 4 volumes.Then for

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the line Lab, the characteristic quantity H describing the line state can be represented as $H=\left[K_a,K_b,P_a,P_b\right]$ where K_a represents the amount of remote signaling state of the first end of the line Lab., K_b represents the amount of remote signaling state at the end of the line Lab., P_a represents the amount of telemetry state of the first end of the line Lab, P_b represents the amount of telemetry state at the end of the line Lab. These feature quantities can be used to invert the node incidence matrix for topology recognition.

III.Graphical Attention Network

3.1Concept, Characteristics of Graph Attention Networks

Graph attention network (GAT) is a network structure that combines graph convolution and attention mechanisms. Compute attention on the input to be processed graph itself. Introduce the idea of attention based on the GCN-based processing graph to calculate the importance of each neighboring node to it, and then get the whole network information from the local information. It is also computationally efficient by stacking these hidden self-attentive layers to obtain the features of the neighboring points, avoiding a large number of matrix operations. When each node updates the output of the hidden layer, the attention is computed on its neighbor nodes. The goal is to assign different weights to each neighboring node, thus focusing on nodes with a more substantial role and ignoring nodes with a smaller part. Each node computes attention in parallel with its neighbors and can assign arbitrary weights to neighboring nodes.

It can be seen that when a node is approximated to an adjacent node feature measure, the primary node feature measure is mostly retained in the updated node feature measure by attentional computation. When there are a few anomalies in the feature quantity of neighboring nodes, the attention mechanism will directly affect the weight of the node that makes the abnormal state and reduce the influence of the significant feature quantity. For topological data, when missing features are describing the line state, the introduction of the attention mechanism can avoid the effect of missing features and ensure the accuracy of node classification. When there is an individual line with an entirely different feature quantity from its neighboring lines, the introduction of the attention mechanism can also reduce the influence of neighboring lines on the lines themselves, and ensure the update of the original features of the lines and the accuracy of node classification.

3.2Architecture of the Graph Attention Network

The graph attention network architecture is similar to a neural network. The input layer of the graph attention network is a set of feature vectors. In a power network topology, each line has four characteristic quantities. Taking them as inputs:

$$H=\left\{h_1,h_2,\cdots,h_n\right\},h_i\in\mathbb{R}^r \tag{1}$$

Where H stands for the set of feature vectors, h_i stands for the i-th feature vector, n stands for the

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number of nodes, and r stands for the dimension of the feature vector.

To obtain the output features, the input features are first transformed once, and a weight matrix is trained on all nodes: $W \in \mathbb{R}^{r' \times r}$. The weight matrix represents the relationship between the input r features and the input r' features.

A self-attentive mechanism is applied to each node, and the attention coefficient is calculated as follows:

$$u_{ij} = a\left(Wh_i, Wh_j\right) \tag{2}$$

Where $a(\bullet)$ represents a function, and the formula indicates the importance of node j for node i.

Based on the connotations of GAT, we introduce marked attention, which applies the attention mechanism to the graph structure. The implication is that attention is assigned to node i that is directly related to it. To make the attention coefficients easy to compute and compare, this paper applies the softmax function to regularize the attention weights:

$$a_{ij} = \frac{\exp\left(LeakyRelu\left(a^T\left[Wh_i \| Wh_j\right]\right)\right)}{\sum_{k \in N_i} \exp\left(LeakyRelu\left(a^T\left[Wh_i \| Wh_k\right]\right)\right)} \tag{3}$$

$\left[Wh_i \| Wh_j\right]$ represents a join operation between two vectors.

Having obtained the normalized attention coefficient, we calculate the linear combination of its corresponding features. The above results are taken as the final characteristic quantity for each node:

$$h_i' = \sigma\left(\sum_{j \in N_i} a_{ij} Wh_j\right) \tag{4}$$

The architecture of Graph Attention Networkis shown in Fig 1.

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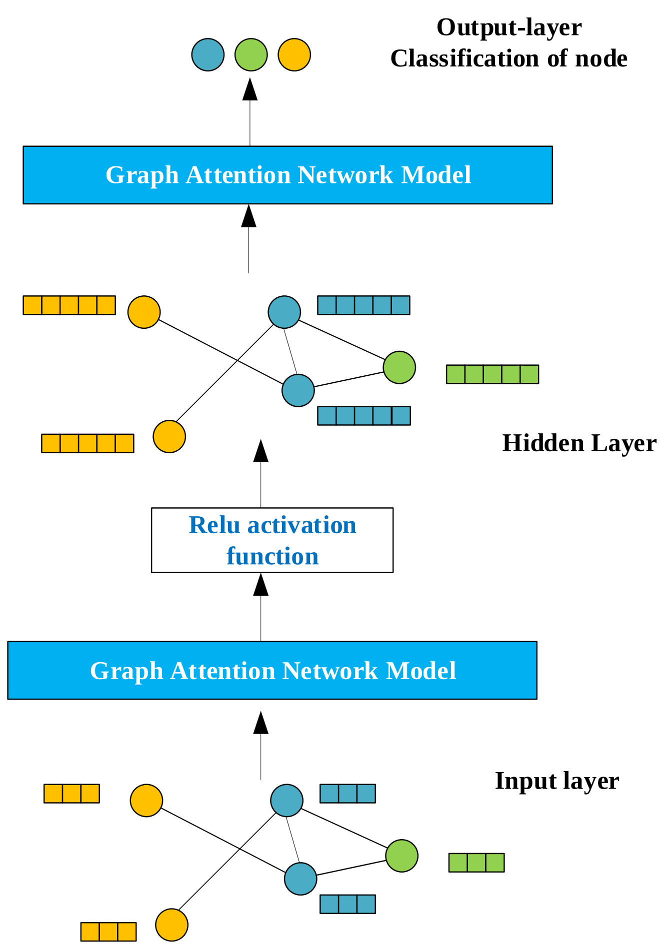

Fig 1:Graph attention network model structure

IV. METHODS OF OWER NETWORK TOPOLOGY IDENTIFICATION

The topology consists of vertices and edges. For power network topology, as long as the determination of the existence of edges is completed, the node incidence matrix can be obtained, thus completing the topology identification. So in this paper, the traditional vertex-edge-vertex expression is changed to the edge-vertex-edge form. We take the line as "vertex," node as "edge." The topology is generated directly after judging the line connectivity in this form.

The process is as follows:

1.According to the power of line P_{ij} P_{ji}, the line switching volume K_{ij} K_{ji}, the formation of a

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description of the line characteristics of the matrix: $x_{ij}=\left[P_{ij} \quad P_{ji} \quad K_{ij} \quad K_{ji}\right]$, where P_{ij} P_{ji} are the measured power values S_{ij} S_{ji} arethe description of the line double-ended switch open state. When the switch is closed for 1 when the switch is open for 0.

2. The P_{ij} P_{ji} in h_{ij} are normalized to form $\hat{h}_{ij}$ such that the eigenvalues in $\hat{h}_{ij}$ are guaranteed to be between [-1,1], such that all $\hat{h}_{ij}$ are aggregated into H, $H \in \mathbb{R}^{N\times 4}$, N is the total number of lines.

3. We classify and label the lines by the number of features. These data are used to test the training of graph attentional networks.

4. Line as vertex, node as the edge. We search for direct line connection relationships based on this form and then compute attention coefficients for each line.

5. We set an as the maximum number of iterative computations $IT_{\max}$, substitute the feature matrix H, the initial weight matrix W0, and the attention coefficient aij into the feature transfer equation, calculate to obtain $H^{'}$, Constantly modifying the weight matrix with $\left\|H^{'}-H\right\|$ as the loss function. After iterative computation, the weight matrix within each hidden layer is obtained. This weight matrix represents a self-trained decision rule that can be used directly to determine line connectivity.

6. After the connectivity determination, we update the node incidence matrix and generate the topology by deduction. Besides, the generated topology is analyzed based on a deep search and other methods. In turn, we can determine if there are isolated nodes if there are isolated islands in operation.

V. EXPERIMENTAL RESULTS

5.1Application in the IEEE57 Node System

In this paper, the IEEE57 node system is used as an example. This systemconsists of 57 nodes and 80 branches. We first generate 500 training samples with the same tidal distribution by power flow calculation. For each sample, five lines are randomly ingested as disconnected, and 15 lines are missing some attribute values.

We label the feature matrices of the 400 training samples. The labeled category one lines are connected; the labeled type 2 lines are lines that are related but have conflicting information in the feature matrix; the labeled type3 lines are disconnected. Finally, 100 samples are unlabeled.

We trained 400 labeled samples as surrogate input graphs in the attentional network. Additional 100 labeled samples are as tests. The rules make the right decision learned from the graph attention network to

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compare the ingestion topology with the generation topology and test the effect.

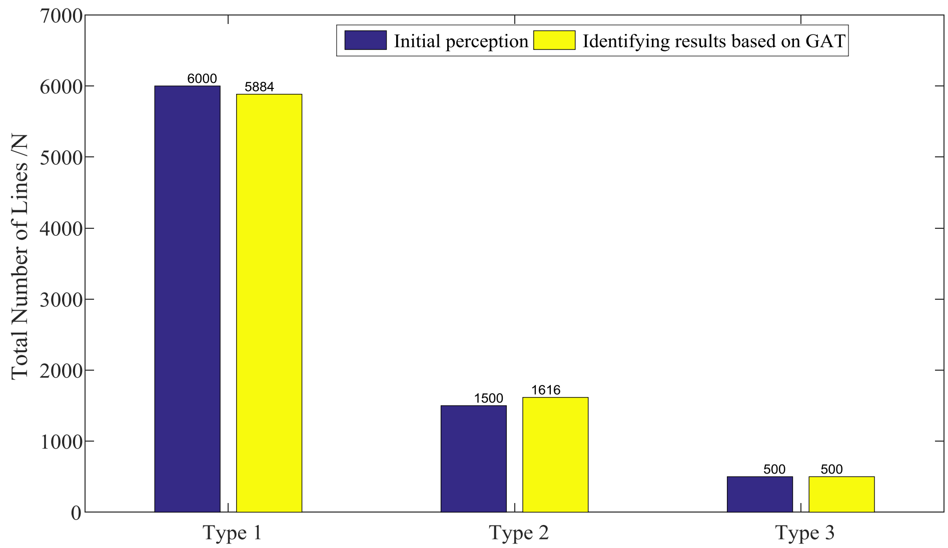

Fig 2: Comparison of GAT-based network topology identification results with the original perception

It can be seen that power network topology identification results based on GAT show in Fig 2. For the disconnected lines of the initial ingestion (Type 3), the results of this method are consistent with the initial ingestion. It means that the method can accurately identify the disconnected lines. For type 2, with 100 samples, the total number of broken lines is 1500, and 1616 lines are determined based on the GAT, which is 116 lines different from the initial ingestion. For Type 1, the total number of lines is 6000, but 5884 lines are identified—a total of 8000 lines for 100 samples. The total number of lines that cannot be determined accurately by this method is 236, accounting for 2.95% of the total number of lines, and the identification accuracy is 97.05%. Although the identification accuracy is not 100%, this method can still identify the disconnected lines accurately, and the resulting topology is credible.

After converting the number of features reflected in the above test sample data into grid data, the random forest algorithm identifies the line state with the following results in Fig 3.

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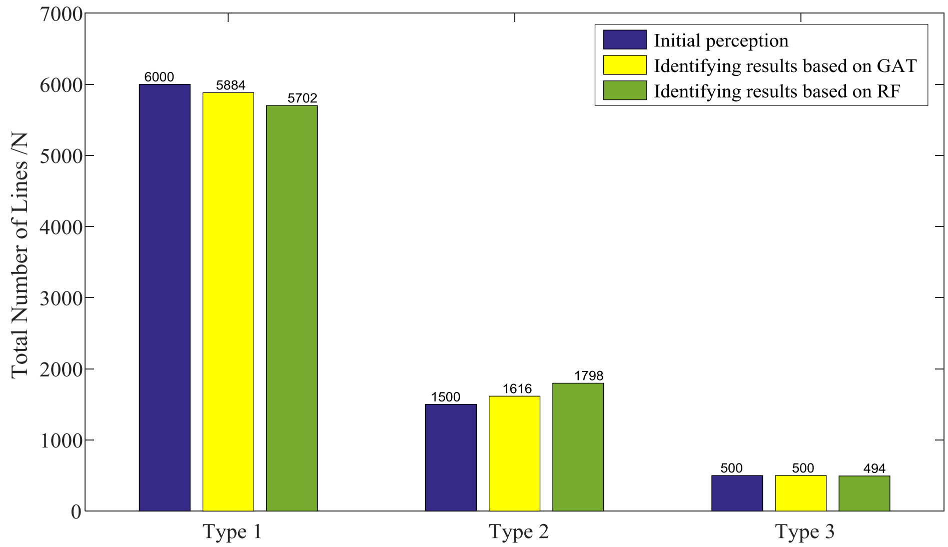

Fig 3: Comparison of random forest identification results with the method in this paper

As can be seen from the above figure, the random forest precision in terms of classification accuracy is only 92.48%, which is lower than the method in this paper and fails to make an accurate determination of open lines.

5.2Application in a Real System

The method in this paper is applied to a provincial network. The network consists of 132 nodes, 181 equivalent branches. The data recording time interval is 1 min. We topologically identify the actual power grid for one month of data. The identification results of each cross-sectional line state can be expressed as a 181×1 column vector consisting of 0, 1. The position corresponding to the line disconnect is marked 0. The corresponding place of the line in operation is marked 1. Then the results of line continuity identification on the timing are shown in Fig 4.

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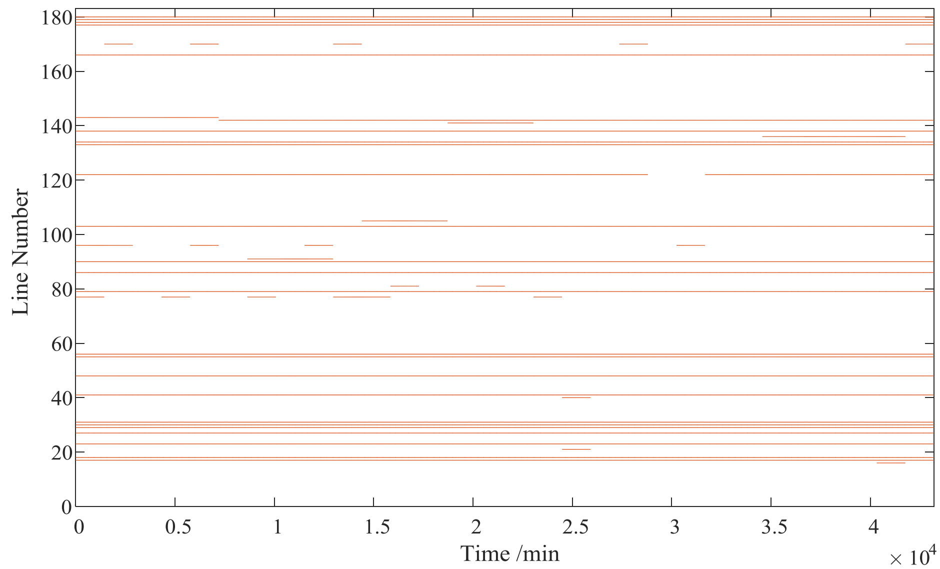

Fig4:Actual grid line in operation/disconnect status timing diagram

In the above figure, the red color block indicates that the line is in a disconnected state, and the white color block suggests that the line is in operation. It can be seen from the statistics that a total of 24 lines have been in the disconnected state during the month, and 13 lines have intermittent changes in the state. The topology can be generated from the corresponding node incidence matrix in the figure above. It is statistically evident that the topology consists of two isolated networks and 13 remote nodes under this period. Isolated network 1 contains 75 nodes and 95 lines in operation. Isolated network 2 contains 44 nodes and 62 lines in operation. It can be seen that the graph attention network-based method identifies the line connectivity and not only generates the topology but also tracks the topology changes in the timing.

VI. CONCLUSION

In this paper, we identify the power network topology based on the graph attention network. Validated by simulation systems and actual power grid, graph attention network-based power network topology identification method does not requiredata conversion. The learned rules allow for theright determination of transmission line connectivity. Since the correlation between samples is taken into account, it can be seen that the accuracy of this method to identify topology is higher than the traditional method,basing on the statistical results. By applying the approach to the actual power grid, we find that this methodis effective in identifyingwhether there is an isolated island operation in the network topology and in trackingchanges in the network topology. This approach provides a good pre-foundation for data-based analysis of the power system operational situation.

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