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A graph neural network-based topology identification and reconfiguration method for electrical and electronic power distribution systems in a big data environment

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ABSTRACT

Accurate distribution system topology is of great significance for distribution network planning operation and analysis. This project constructs a distribution system network model, applies graph convolutional network and graph attention network in graph neural network, and designs the topology identification method of distribution system. On this basis, a reconfiguration model of the distribution system is given, and the network structure after topology identification is used for trend calculation, and the model reconfiguration is realized by using the extensive learning quantum evolutionary algorithm. Through experimental analysis of several test systems, it is found that the topology identification F1 values of this paper's method are all above 0.9, which are 5.64% to 29.64% higher than other methods, confirming the good accuracy and robustness of the GNN topology identification model. In addition, the CLQIEA method can give the correct distribution system reconfiguration optimization scheme, which reduces the network loss to a larger extent and improves most of the node voltage values, and the network loss decreases by 31.91% and 56.11%, and the voltage values are improved by an average of 1.95% and 1.23% in the two test systems, which makes the power supply of the distribution system of a higher quality, and the operation of the power supply system is more economical, which is important for the distribution automation and the power supply department's optimal scheduling is of great significance.

Keywords: graph neural network, CLQIEA algorithm, topology identification, reconstruction method, distribution system

1. Introduction

With the development of social economy, the proportion of capital investment in China's power grid has increased, and to ensure the reliable operation of China's electronic and electrical equipment, and to maximize the protection of people's power needs, a major reform of the power grid system is

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needed [1-3]. This represents the need for both distribution quality and power supply quality to be improved on a large scale and in both directions, to improve the quality of power supply through the basic function of relay protection in the distribution system, and at the same time to provide effective measures to strengthen the distribution relay protection and to promote the stable development of electric and electronic equipment [4-5]. As a complex large-scale nonlinear system, one of the most important tasks of the power distribution system is how to maintain operational stability [6]. Without affecting the normal operation of the distribution system, the quality of power electronic equipment to ensure power generation and transmission is improved [7]. At the same time, it is also necessary to focus on the security of the use of the power distribution system, once the power distribution system loses stability, then the consequences to be borne are unimaginable [8-10]. For electric power enterprises, it is necessary to continuously carry out reform and innovation, add more efficient and scientific power electronic equipment, and reduce the probability of safety accidents. In order to improve the stability of the operating status of the power system and ensure its normal function, then the reform and innovation of the distribution relay protection system is needed to increase the overall development and management costs, and truly comprehensive coverage of power supply relay safety measures [11-13].

Topology identification is one of the basic functions that energy management systems (EMS) and distribution systems need to implement, and recording accurate topology and line parameters is an indispensable input for trend calculation, state estimation, and other advanced applications, which is an important prerequisite for improving the level of power supply services and optimizing the power users' experience of electricity consumption [14-17]. In order to adapt to the growing demand for electricity, distribution networks often need to be expanded, resulting in the addition of new substations and inlet/outlet lines, the increasing node size of the distribution network, and a large number of power lines, leading to a complex distribution network topology connectivity relationship and a flexible and variable operation structure [18-20]. As early as the end of the twentieth century, the topology identification of the distribution system has attracted the attention of related scientists and power engineers, and some scholars have abstracted the key electrical equipment and power lines in the distribution system as points and lines, and set up a correlation table to record the topological information of the distribution network according to the layout characteristics between nodes and the line operation status [21-23]. Since the distribution network accounts for a relatively small number of lines with frequent changes in opening and closing states in daily operation and maintenance, the association table can be corrected locally accordingly by detecting the line switching actions to track topology changes and improve the efficiency of distribution system topology management [24].

In addition, some scholars proposed a matrixized representation of network topology and solved the actual topology of the distribution network by matrix analysis [25]. The traditional topology identification methods, mainly include tree search method and matrix operation method. Literature [26] addresses the inadequacy of the presence of potential nodes in the traditional low-voltage distribution network (LVDG) for topology identification in distribution networks and proposes to utilize the tree-based search method for generating candidate topologies and to evaluate the accuracy of the candidate topologies using the Bayesian information criterion. Literature [27] used Gradient Boosting Decision Tree (GBDT) combined with Attribute Weighted Simple Bayes (AWNB) to improve the accuracy and reliability of topology identification for distribution systems. Although the tree search method improves the speed of topology identification, it still takes up a large amount of memory for distribution systems with more complex line connection relationships, and the efficiency of topology identification needs to be further improved.

In terms of matrix operation algorithm, literature [28] proposed a complex-valued Laplace matrix estimation method based on constrained maximum likelihood estimation (CMLE) for the estimation of node conductance matrices, so as to realize the accuracy of topology identification of distribution systems. Literature [29] reconstructs the topology of a networked linear power system with potential nodes by observing the power spectral density matrix obtained from the nodes, and the inverse decomposition into sparse low-rank components. The matrix operation algorithm can identify the network topology more systematically and intuitively, but it requires high storage capacity of the computer, takes longer time for topology identification, and when a new node is added to the distribution network, the order of the matrix increases, and the computation of the matrix operation algorithm rises significantly, so there are some limitations in practice [30-31].

With the continuous improvement and upgrading of advanced measurement architecture and power consumption information collection system, as well as the wide deployment of intelligent distribution system, power companies can obtain minute-level user power consumption data and system trend information in the data center, and many scholars have proposed a variety of distribution system topology parameter identification methods based on deep learning framework [32]. Literature [33] constructed a novel distribution system topology identification method based on convolutional neural network (CNN) in deep learning through multi-label classification method, and verified the method with high topology identification accuracy in an improved IEEE 123-node distribution network. Literature [34] also designed a topology design method to analyze the abstract edge information (called texture) in the feature graph through the steps of hidden layer design, Kernel design and Weight initialization based on CNN. Graph Neural Network (GNN), is a deep learning framework specialized in processing graph-structured data. Literature [35] proposes a knowledge graph and GNN-based topology recognition method for power grids, which is trained with fault-tolerant features of labeled nodes (lines) by GNN, and utilizes the knowledge graph to quickly mine possible connections between entities and generate graph-structured data. Unlike other deep learning frameworks, GNN addresses the limitation that traditional topology recognition methods lack data tolerance mechanisms. Therefore, the application of GNN to topology recognition and reconstruction of electrical and electronic distribution systems is also the main research line of this paper.

In this paper, we first introduce the distribution network topology-related model and topology recognition problem description, and propose a deep learning-based distribution network topology recognition method from the perspective of big data. Then, topology identification based on graph neural network is realized by constructing a distribution system network model and extracting features using graph convolutional network and graph attention network. Taking the minimum network power loss as the objective optimization function of distribution system reconfiguration, on the basis of topology identification, the forward back generation method is used to carry out the trend calculation of distribution network, set the constraints of distribution network reconfiguration, and then the extensive learning quantum evolutionary algorithm is used as the implementation algorithm to complete the construction of the distribution system reconfiguration method. Then simulation experiments are carried out with several distribution systems as case studies to explore the topology identification effect of different methods, and the effects of measurement error, number of samples and different topologies on the model identification effect, to test the topology identification performance of the GNN model. Finally, tests are conducted in IEEE33 and PG&E69 node systems respectively to compare the active network loss and minimum node voltage of different methods, and analyze the reconfiguration optimization effect of the CLQIEA method on the distribution system.

2. Electrical and electronic distribution system topology identification issues

As a direct channel connecting the transmission grid and users, the safety, reliability, and automation degree of the electrical distribution system directly affects the users' experience of electricity consumption. As an important part of the distribution automation system, topology identification and reconfiguration optimization of the distribution network is a guarantee for the safe and reliable operation of the distribution network, so the research on topology identification and reconfiguration optimization of the distribution system has become a topic of great concern to scholars.

2.1. Topological model and representation

The electrical and electronic distribution system can be divided into high voltage (220, 110, 63, 35kV), medium voltage (10kV) and low voltage distribution network (380/220V) according to the voltage level. The network structure of the distribution system is complex, with a wide variety of equipment components, mainly including substations, low-voltage loads, feeders, disconnecting switches, contact switches, distribution transformers and reactive power compensation devices and other distribution equipment and other distribution auxiliary devices.

The distribution system is generally closed-loop design and open-loop operation, and the current structure of the distribution network is generally radial or ring-shaped. Considering the flexibility of distribution system operation and power supply reliability, the distribution system structure adopts closed-loop design. The open-loop operation of the distribution system is, on the one hand, to limit the size of the short-circuit current under the fault condition, and on the other hand, to be able to isolate the fault in time, prevent the expansion of the scope of fault outage, and guarantee the reliability of power supply to users. For areas with high power supply reliability, such as urban distribution networks, industrial and commercial parks, etc., the topology of the distribution system is generally a ring topology with alternate power supply paths, while for rural areas with lower power supply reliability requirements, the topology of the distribution system is generally a deep radial structure.

The physical network topology of the distribution system is generally more complex, with a wide variety of equipment components and poor visualization, which does not facilitate direct topology analysis and state estimation. In order to simplify the topology of the distribution system and carry out fast and effective topology analysis, the physical topology of the distribution system is generally simplified and equated to a topology diagram model composed of points and lines, i.e., nodes represent substations, busbars, distribution transformers and loads, and lines represent branch feeders, disconnect switches, contact switches and other components.

2.2. Description of the topology identification problem

The essence of the distribution system topology identification problem is to accurately identify in real time the commissioning status of busbars and distribution transformers, as well as the on/off status of sectionalized switches and contact switches in the distribution system. From the point of view of matrix algebra is to determine the value of each position element in the matrix, the topology of the distribution system under different operating modes is shown in Figure 1 below, two different operating modes of the same structure of the distribution system, its topology is also different, the adjacency matrix is expressed as A_{adj1} and A_{adj2}, the topology identification is the ability to accurately get Each element of the adjacency matrix is 0 or 1 in the current operation mode, and when each element of the adjacency matrix is determined, it can be mapped to obtain the real-time operation topology of the power distribution system.

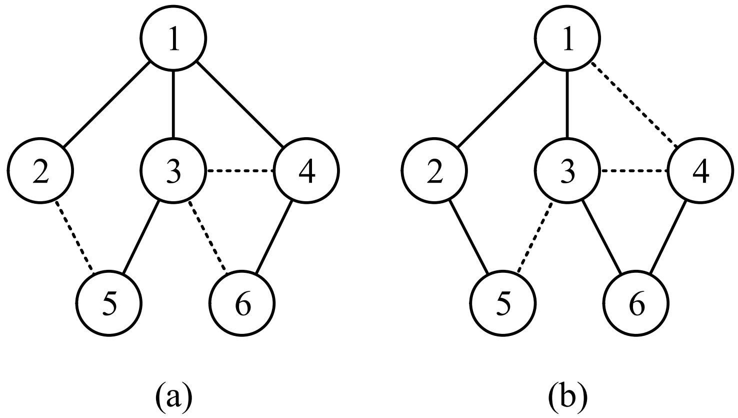

Fig. 1. Topology of the distribution network in different operating modes

With the acceleration of the construction process of smart grid, smart meters, intelligent distribution terminals, PMU and other intelligent equipment in the distribution network automation system are more widely used, based on these intelligent measurement devices, the distribution system is recording and generating massive power grid operation data all the time, and the data value of subsystems such as power generation management, transmission monitoring, distribution operation, load control, and electricity fee management can be mined to improve the performance of distribution network topology identification with the distribution automation system.

With the development of data science methods represented by big data and deep learning technology in smart grids, deep learning methods can be considered as an alternative to the traditional topology identification model, and accurate and efficient online identification methods of distribution network topology can be proposed by mining the dependency relationship between distribution system operation data and distribution network topology. Based on the above analysis, the problem of distribution system topology identification can be reduced to the problem of using deep neural networks to map the topology-dependent measurement data of distribution depth with the contact switch and sectionalized switch on/off states in different operation modes of distribution depth.

3. GNN-based topology identification and reconfiguration methods for distribution systems

In this chapter, the distribution system network model is constructed, and the graph neural network (GNN) is applied to realize the network topology identification of the distribution system. On this basis, the framework of distribution network reconfiguration method is given, and each module is analyzed in detail, mainly including network structure topology identification, current calculation, constraints analysis, etc., and the extensive learning quantum evolution algorithm is used to realize the reconfiguration of distribution system.

3.1. GNN-based topology identification

3.1.1. Graph neural network model:

1) Graph Convolutional Network (GCN). The core of Graph Convolutional Network (GCN) lies in updating the feature representation of a node through graph convolution operation. This operation uses the features of the node and its neighboring nodes, which are aggregated through a weight matrix to achieve feature transfer and update. The expression is as in equation (1):

$$h_v^{(l+1)} = \sigma(D_v^{-\frac{1}{2}} A D_v^{-\frac{1}{2}} h_v^{(l)} W^{(l)}) \tag{1}$$

where $hv^{(1)}$ denotes the feature vector of node v in layer 1, A is the adjacency matrix of the graph, Dv is the diagonal element of the degree matrix of node v, $W^{(1)}$ is the weight matrix of layer 1, and σ is the activation function. This formulation ensures consistency and smoothness of feature updates.

In the application of power distribution system, GCN is able to capture the complex relationship between nodes and effectively recognize the network topology. Its advantage lies in its ability to handle non-Euclidean data and adapt to the complex network structure of power distribution systems. The graph convolution operation allows node features to be aggregated through neighboring nodes, enhancing the expression of features. In addition, GCN is able to achieve hierarchical learning of node features, providing a powerful feature representation for topology recognition.

2) Graph Attention Network (GAT). Graph Attention Network (GAT) dynamically adjusts the feature aggregation weights among nodes by introducing an attention mechanism. As in equation (2):

$$h_v^{(l+1)} = \sigma(\sum_{u \in N(v)} \alpha_{vu} W^{(l)} h_v^{(l)}) \tag{2}$$

where $hv^{(1)}$ denotes the feature vector of node v in layer 1, $N(v)$ is the set of neighboring nodes of node v, a_{vu} is the attention coefficient between node v and u, $W^{(1)}$ is the weight matrix of layer 1, and σ is the activation function. The attention coefficients a_{vu} are usually passed as in equation (3):

$$\alpha_{uu} = \frac{\exp(a^T [W^{(l)} h_v^{(l)} W^{(l)} h_u^{(l)}])}{\sum_{k \in N(v)} \exp(a^T [W^{(l)} h_v^{(l)} W^{(l)} h_k^{(l)}])} \tag{3}$$

3.1.2. Network modeling. In the complex network topology identification of power distribution system, the network model construction is the foundation. The model abstracts the actual distribution system as a graph $G = (V, E)$, where V is the set of nodes and E is the set of edges, through the precise definition of nodes and edges. Nodes $v \in V$ represent physical entities such as distribution stations or transmission lines, and edges $e \in E$ represent electrical connections between entities.

Definition of nodes and edges: each node v possesses a feature vector xv containing its attributes such as voltage level and load. Edge e connects two nodes and represents the electrical connection between them. The adjacency matrix A of the graph describes the connection status between nodes, A_{ij} is 1 indicating that nodes i and j are directly connected, and 0 otherwise.

Network feature extraction: the feature vector xv of a node is updated to $hv^{(1+1)}$ by graph convolution operation, aggregating the features of its neighboring nodes. The graph convolution operation is expressed as in equation (4):

$$h_v^{(l+1)} = \sigma(\sum_{u \in N(v)} \frac{1}{c_{vu}} W^{(l)} h_u^{(l)}) \tag{4}$$

Where $hv^{(l)}$ is the feature vector of node v at layer 1, N(v) is the set of neighboring nodes of node v, c_{vu} is the normalization coefficients, $W^{(l)}$ is the weight matrix, and σ is the activation function.

The connection relationship between nodes and edges can be visualized in Fig. 2, where the size and color of nodes can indicate different attributes such as load or voltage level. The thickness of the edges can indicate the strength or current capacity of the connection. In the figure, node v and its neighbor node u are connected by edge e, and the feature vector $hv^{(l+1)}$ of node v will aggregate the features of its neighbor nodes during the feature extraction process.

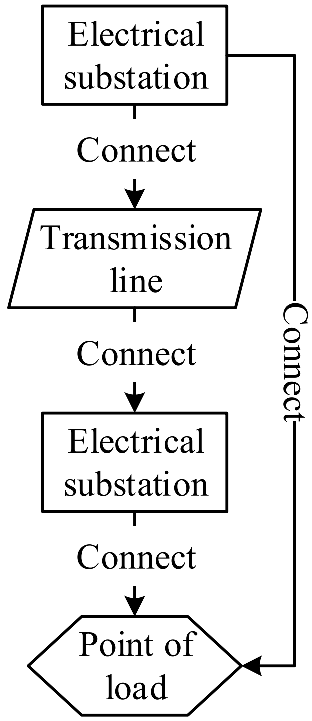

Fig. 2. System model network

3.1.3. Feature Representation and Learning. For distribution systems, node characteristics include not only physical attributes such as voltage level and load capacity, but also topological attributes such as the degree of the node (i.e., the number of connected edges). Together, these features form the initial feature vector of a node xv. Through graph convolution operation, the feature vector of a node is updated at each layer of the network to reflect its position and role in the network. The graph convolution operation is as in equation (5):

$$h_v^{(l+1)} = \sigma\left(\sum_{u \in N(v)} \frac{1}{c_{vu}} W^{(l)} h_u^{(l)} + E_{vu}\right) \tag{5}$$

Where $hv^{(1)}$ is the feature vector of node v at layer 1, N(v) is the set of neighboring nodes of node v, c_{vu} is the normalization coefficients, $w^{(1)}$ is the weight matrix, and σ is the activation function.

Edge features can include electrical attributes such as current capacity, resistance, etc., which are essential for understanding the transmission capacity and vulnerability of the network. The representation of edge characteristics can be realized by the weight matrix of the edge E, where E_{ij} denotes the eigenvector of the edge e_{ij}.

3.1.4. Topology Recognition Algorithm. The topology identification algorithm aims to accurately identify the network structure of the power distribution system through a graph neural network. The process includes node feature initialization, graph convolution operation, topology feature extraction and topology structure learning. Initially, node feature vectors are defined by their physical and topological properties. Through a multi-layer graph convolution operation, node features are updated to include information about their neighboring nodes, which in turn leads to the extraction of topological features. Eventually, the network topology is identified and optimized through supervised or unsupervised learning techniques. As in equation (6):

$$h_v^{(l+1)} = \sigma(D_v^{-\frac{1}{2}} A D_v^{-\frac{1}{2}} h_v^{(l)} W^{(l)}) \tag{6}$$

where $hv^{(1)}$ and $hv^{(l+1)}$ denote the node eigenvectors at layers 1 and $l+1$, respectively, A is the adjacency matrix, Dv is the degree matrix of the node v, and $W^{(1)}$ is the weight matrix at layer 1.

3.2. CLQIEA-based Distribution System Reconfiguration

3.2.1. Reconstructing the optimization mathematical model. Reconfiguration optimization as an important measure and method for the economic and reliable operation of the distribution system, in the optimization, it is necessary to establish the objective function, and then solve it to achieve the purpose of optimization. The following are several important and practical applications of the objective function:

1) Minimum network loss: $\min f = \sum_{i=1}^{l} \frac{R_i (P_i^2 + Q_i^2)}{U_i^2}$, the branch i resistance is denoted by R_i, U_i, P_i, Q_i denote the voltage, active and reactive power at the end nodes of branch i, respectively, and the total number of branches is l.

2) Load equalization: $\min f = \sum_{i=1}^{l} | \frac{S_i}{S_i^{\max}} |^2$, and S_i and $S_i^{\max}$ denote the branch i-loads and the maximum capacity respectively. The system network loss and overload probability are reduced by shifting the load.

3) The average supply unreliability rate is minimized, i.e., the reliability is maximized: $\min F_{ASUI} = \sum_{i=1}^{N_p} \frac{U_i N_i}{8760 N_T}$, in which N_T, N_p, N_i denote the total number of system subscribers, the number of system load points and the number of subscribers at load point i and the annual outage time, respectively, by which the number of outages and outage time of the subscribers can be reduced to improve the level and quality of service.

Usually, when reconfiguring, not only a single optimization function can be selected according to the operational requirements, but also several objective functions can be combined as the final optimization function. In this chapter, the minimum network power loss is selected as the objective optimization function for reconfiguration in each time period.

3.2.2. Overall framework of the reconstruction methodology. The framework of the distribution system reconfiguration methodology consists of two modules: the main program and the algorithm optimization. It is specifically subdivided into the following parts: inputting the forecasted load and distribution network raw data information, network topology identification, constraints analysis, distribution network tidal current calculation and extensive learning quantum evolution algorithm. The overall framework of the distribution system reconfiguration method is shown in Fig. 3. Among them, the network topology identification module adopts the topology identification method based on graph neural network in the previous section. The raw data of power distribution mainly include branch resistance and reactance values of the network, node active power and reactive power, which are processed by the main program module as input data and then transferred to the algorithm optimization module. The above module can be subdivided into several aspects such as inputting required data, population initialization, observation, adaptation evaluation, updating quantum gates, identifying topology, analyzing constraints, and forward back generation trend calculation, and integrating the above sub-modules to complete the optimization of distribution network reconfiguration and ultimately outputting reconfiguration scheme.

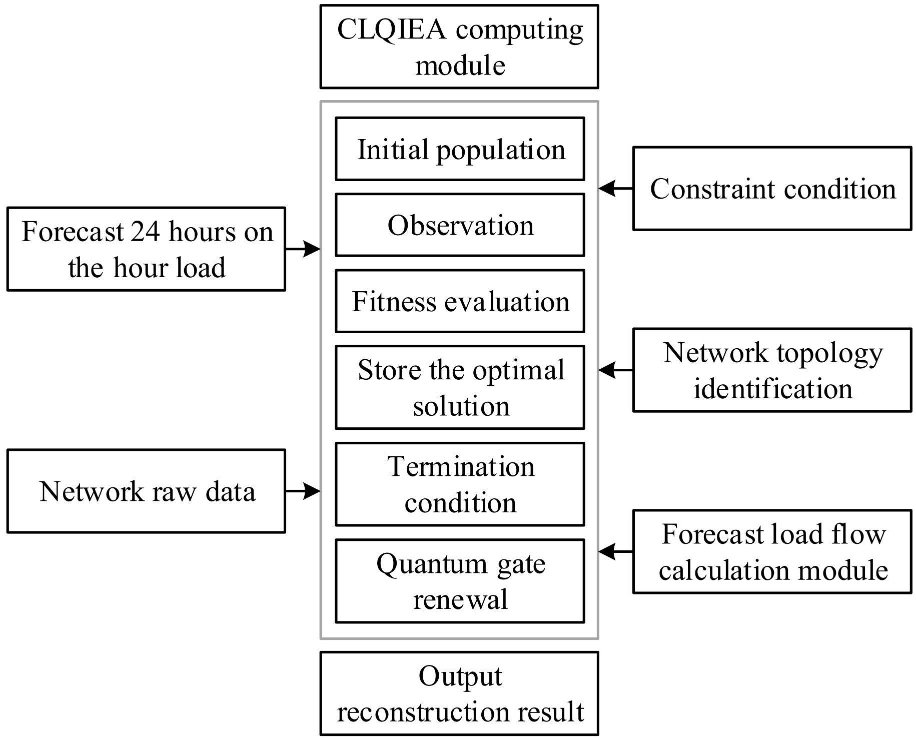

Fig. 3. The overall framework of the distribution system reconstruction method

3.2.3. Distribution network current calculation. After completing the topology identification of the distribution network, the next step is to carry out the trend calculation of the whole network to determine the operating conditions and electrical status of the whole network, so as to ensure the reliability, rationality and economy of power operation.

In this paper, in the reconfiguration process, the feeder is used as a unit to calculate the trend of the distribution system using the forward and back generation method, which is a relatively simple principle, convergence speed is very fast, and is suitable for the distribution system trend calculation.

For a power distribution system with a total number of nodes N, its topology, root node voltage U_0, load of each node $P_{Li}jQ_{Li}$ and the impedance of each branch $R_{ij}jX_{ij}$ are all known quantities, that is, given, and the quantities to be solved are the voltages of each node U_i, the currents flowing through each branch I_{ij}, etc.

1) Forward to solve for each node load current and branch current in turn. Nodal currents:

$$I_j = \left(\frac{P_{Lj} + jQ_{Lj}}{U_j} \right)^* \tag{7}$$

If k is the end node of this feeder:

$$I_{jk} = I_k = \left(\frac{P_{Lk} + jQ_{Lk}}{U_k} \right)^* \tag{8}$$

If not, then yes:

$$I_{jk} = I_k + \sum_{veD(k)} I_{kv} \tag{9}$$

$D(k)$ is the set consisting of all child nodes with k as parent.

The injected current I_{ij} at each branch endpoint is:

$$I_{ij} = I_j + I_{jk} \tag{10}$$

2) Generate back to solve for each node voltage of the system in turn. The voltage at a node of the desired level is equal to the voltage at the node connected to it at the previous level minus the voltage drop on the branch formed by the two nodes. The back generation process of sequential calculation uses the following equation:

$$U_j = U_i - I_{ij}(R_{ij} + jQ_{ij}) \tag{11}$$

until the set convergence condition is satisfied.

3.2.4. Reconfiguration constraints. Because of the limitations of the distribution system network structure as well as the trend calculation, the distribution system has to fulfill certain constraints during reconfiguration.
1) Trend constraints. All nodes and branches of the distribution system must satisfy the laws of KVL and KCL, while the power should be balanced.
2) Topology constraints. Reconfiguration optimization should still ensure the connectivity of each node and avoid ring network and islanding.
3) Voltage constraints:

$$U_{i\min} < U_i < U_{i\max} \tag{12}$$

The node i voltage is described by U_t, and its upper and lower limits are denoted by $U_{i\min}, U_{i\max}$, respectively.
4) Current constraints:

$$I_i < I_{i\max} \tag{13}$$

The current flowing in branch i and the upper limit of allowable current are denoted by $I_i, I_{i\max}$ respectively.
5) Constraints on the number of switching actions

3.2.5. Reconfiguration of implementation algorithms. The extensive learning quantum evolutionary algorithm (CLQIEA) is used to solve the dynamic reconfiguration problem of power distribution system. Quantum evolutionary algorithm (QIEA) is a heuristic optimization and stochastic search method based on the population scheme, CLQIEA algorithm introduces the idea of extensive learning on the basis of QIEA, which makes full use of the rich information of the population and further improves the ability of searching for the global optimal solution.

The specific implementation steps of CLQIEA are as follows:
1) Initialize the evolutionary algebra: $t = 0$.
2) Initialize the population $Q(t)$. Where the length of the chromosome is defined by the programmer according to the predefined problem of the $n*m$ 0~1 matrix generated along with it, then the tth generation of chromosomes can be described as follows:

$$Q(t) = \left\{ q_1^t, q_2^t, \ldots, q_n^t \right\} \tag{14}$$

The size of the population is set to n, the number of evolutionary generations is t, q_j^t is defined as in Equation (15), and m is the length of the chromosome:

$$q_j^t = \begin{bmatrix} \alpha_{j1}^t & | & \alpha_{j2}^t & | & \cdots & | & \alpha_{jm}^t \\ \beta_{j1}^t & | & \beta_{j2}^t & | & \cdots & | & \beta_{jm}^t \end{bmatrix} \tag{15}$$

The initialization $Q(t)$ step where $q_j^o = q_j^f \mid t=0$ are initialized to $\frac{1}{\sqrt{2}}$, $\left|\phi_{q_i}^o\right\rangle = \sum_{k=1}^{m} \frac{1}{\sqrt{2^m}} \left|x_k\right\rangle$, X_k is the kth state of the binary code $(x_1, x_2, \ldots, x_m)$. The x_i is in state 0 or 1 depending on the size of $|\alpha_i^o|^2$ and $|\beta_i^o|^2$ respectively.

3) The observation state $P(t)$ is generated from $Q(t)$. This is one of the more critical steps of QIEA. By observing $Q(t)$ we get $P(t)$ consisting of multiple binary numbers. where $P(t) = \{x_1', x_2', \ldots, x_n'\}, x_j' = b_1 b_2 \ldots b_m, b_i (i = 1, 2, \ldots, m)$ is the binary string obtained after observation.

4) Construct the fitness function to evaluate $P(t)$ individuals, and then store the retained optimal individuals $B(t) = \{b_1', b_2', \ldots, b_n'\}$. Construct the fitness function to evaluate the optimal individual of $P(t)$, it should be pointed out here that in QIEA, the role played by quantum gates is to make the general quantum chromosome close to the optimal quantum chromosome, not to change the optimal individual so we need to find out the quantum chromosome that produces the optimal individual.

5) Determine whether the termination condition is satisfied: yes, then end, otherwise, proceed to the next step.

6) Population individuals for extensive learning, the rotation angle calculation formula is:

$$\Delta\theta_i = sign((x_i - b_i) * (f(x) - f_i(b))) * \Delta\theta \tag{16}$$

$sign$ represents the sign, $b_i, f_i(b)$ the learning objective of the ith quantum bit and its corresponding fitness value, and $\Delta\theta$ the given initial value, so that $\Delta\theta_i$ is determined more simply and efficiently, which in turn applies the following quantum gate to update the population $Q(t)$. The quantum gate is $G = \begin{bmatrix} \cos\Delta\theta_i & -\sin\Delta\theta_i \\ \sin\Delta\theta_i & \cos\Delta\theta_i \end{bmatrix}$, updated bits are $\begin{bmatrix} \alpha_i' \\ \beta_i' \end{bmatrix} = G \times \begin{bmatrix} \alpha_i \\ \beta_i \end{bmatrix}$.

7) $t = t + 1$, go to step 2.

4. Experimental analysis of distribution system topology identification and reconfiguration

4.1. Analysis of topology identification algorithms

4.1.1. Evaluation indicators. In order to judge the effectiveness of the model, the F-score is introduced as an evaluation index for the topology identification results of the distribution system. The connection of each group of nodes is regarded as a binary classification problem, and the evaluation of a connection can be categorized into four cases according to whether the recognition result (connected or unconnected) is consistent with the actual situation: true positive case (TP), true negative case (TN), false positive case (FP) and false negative case (FN). Two metrics, precision (P) and recall (R), are introduced to describe the accuracy and sensitivity of the recognition results. In topology recognition, both FP and FN lead to global topology errors. Therefore, the reconciled mean of P and R is used to evaluate the recognition results, defined as the F1 score, and the accuracy of topology recognition results is positively correlated with the F1 score.

4.1.2. Introduction to the algorithm. In this subsection, the performance of the algorithm will be tested on multiple MV distribution systems and LV distribution systems using multiple case details as follows:

Case 1: IEEE 33 node distribution system is used as the basic topology, defined as IEEE33. Input data for each node is generated by Monte Carlo method and 500 tidal calculations are executed to obtain voltage timing data for each node.

Case 2: IEEE 123 node power distribution system is used to test the effectiveness of the algorithm for a large system, defined as IEEE123. The generation of input data is similar to the IEEE 33 system.

Case 3: An actual 45-node MV distribution system, defined as MV45, is introduced. This system contains 8 branch nodes and 37 LV distribution transformer nodes.

Case 4: An actual LV distribution system with 55 end-users, defined as LV55, is introduced. The distribution system consists of 3 branch boxes and 6 meter boxes with end-users varying from 8 to 11 per meter box.

4.1.3. Calculation results and analysis:

1) Comparative analysis with other models. In order to further validate the accuracy of the models in this paper, the proposed GNN model, as well as the models of mutual information (MI), concentration matrix (CM), coefficient of determination (R2), random forest (RF), and multi-output regression (MOR), were tested on four distribution systems, namely, IEEE33, IEEE123, MV45, and LV55, respectively. The identification results of different models on different test systems are shown in Fig. 4. The F1 scores using the GNN model are higher than the other three models on different test systems, and its F1 results on the four test systems are 0.958, 0.913, 0.961, and 0.915, with an average value of 0.937, which is an improvement over the MI, CM, R2, RF, and MOR models, respectively, by 25.86%, 29.64%, 22.24%, 11.85% and 5.64%, which reflects the superiority of this paper's method for distribution system topology identification.

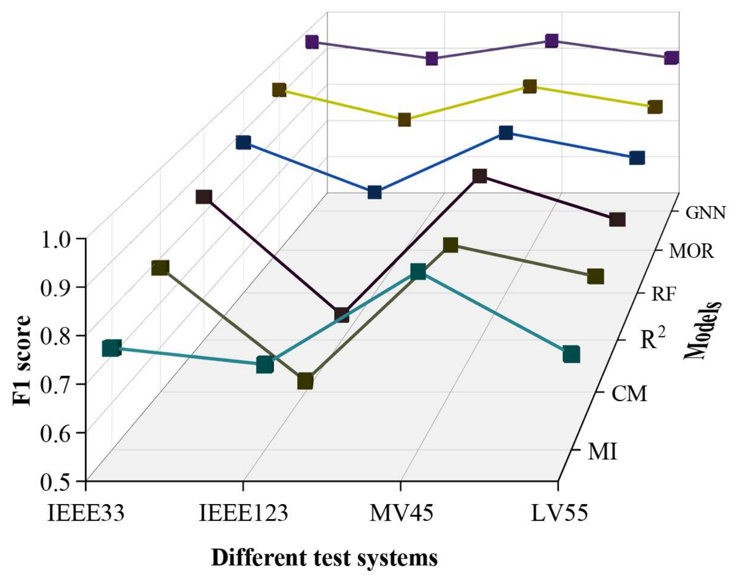

Fig. 4. Identification results of different models on different test systems

2) Influence of measurement errors on results. Measurement error is inevitable in the data collected from the measurement device. According to the relevant standards, the accuracy of power meters is divided into seven levels: 0.1, 0.2, 0.5, 1.0, 1.5, 2.5, and 5.0. In order to test the effect of the GNN method proposed in this paper on the results of topology identification, the test is carried out with the IEEE33 and IEEE123 systems, and corresponding errors are set for the voltage data obtained through trending calculations. After several calculations, the average F1 score under the influence of noise is shown in Fig. 5, where Y denotes with data processing and N denotes without data processing.

In the absence of data processing, the F1 score decreases as the measurement accuracy decreases, and the data quality has a large impact on the identification results. By applying the graph neural network-based method proposed in this paper, the effect of measurement noise can be effectively eliminated. The F1 scores of the IEEE33 and IEEE123 systems are 0.936 and 0.892, respectively, when all data are subjected to 1% noise.The test results show that the measurement error has little effect on the algorithm accuracy when the measurement device meets the standard. The GNN method proposed in this paper can greatly reduce the impact of data quality and improve the accuracy of topology identification.

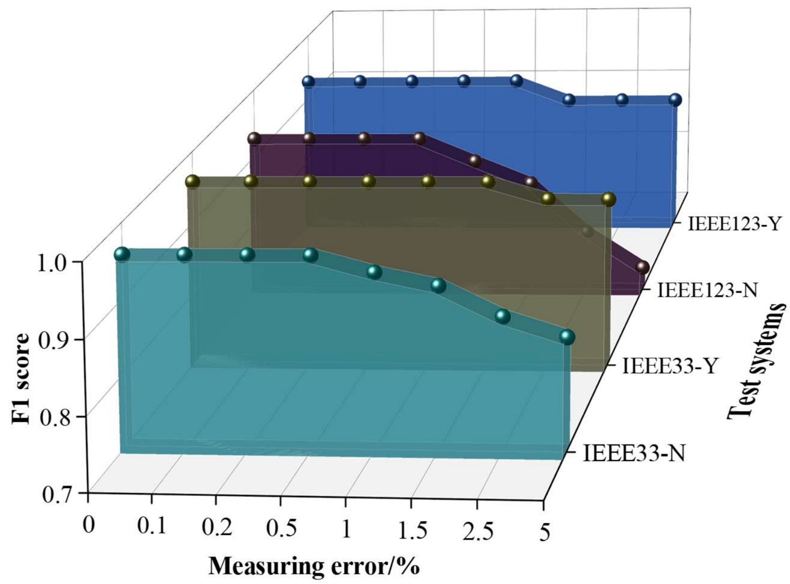

Fig. 5. The average F1 score under noise

3) Effect of sample size on results. In order to evaluate the effect of dataset size on the accuracy of the algorithm, the proposed method was tested in a variety of scenarios with input time periods set from 50 to 550. Figure 6 shows the F1 scores for different systems with various data sizes. It can be noticed that the accuracy is positively correlated with the number of measurement samples. The four tested systems show different sensitivities to the amount of data. For the IEEE33 system, only 325 measurement samples are required to achieve the best estimate, at which point the F1 score is 0.961.

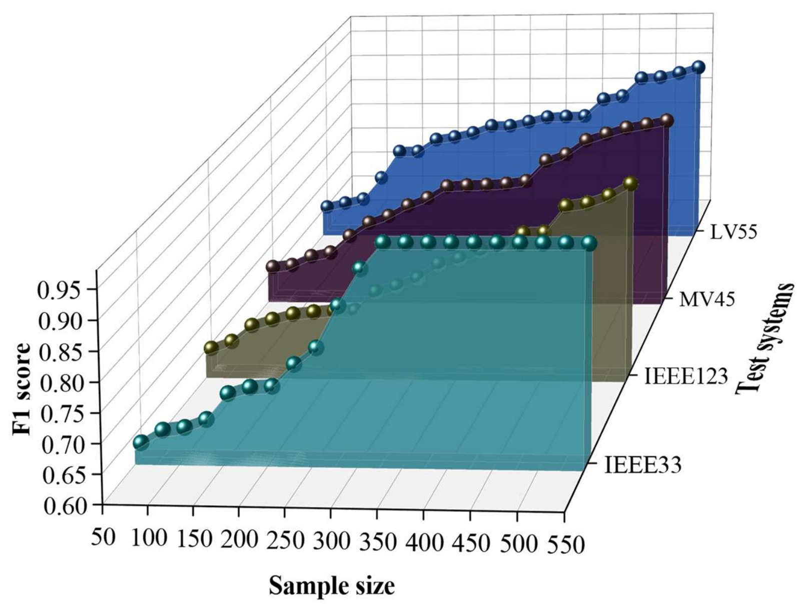

Fig. 6. F1 scores of different systems with various data quantities

4) Effect of different topologies on the results. In order to test the adaptability of the algorithm to different scenarios, several modified 33-node power distribution systems were generated by modifying the topology of IEEE33 to increase the complexity of the topology connections. In these systems, the connections of certain nodes have been randomly changed. Fig. 7 shows the F1 scores of

the recognition results of the GNN algorithm in this paper for different topologies. Topology complexity has an impact on the accuracy of the algorithm. However, the recognition accuracy of various modified IEEE33 power distribution systems is still high, with an average F1 score of 0.921, which demonstrates that the GNN algorithm of this paper is well adapted to various types of complex topologies.

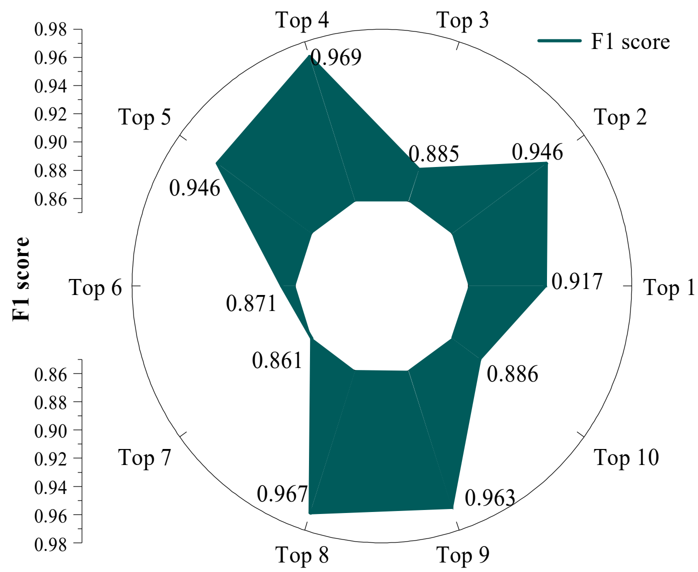

Fig. 7. F1 scores identified by different topologies

4.2. Reconfiguration experiment analysis

In this section, MATLAB software is used to write programs to realize the reconfiguration of the distribution system. The experimental simulation is carried out with IEEE33 node system and PG&E69 node system as an example, and the effectiveness and accuracy of the algorithm is verified through the comparative analysis of the experimental results.

4.2.1. IEEE33 node system. Parameter settings: the chromosome length of the extensive learning quantum evolutionary algorithm (CLQIEA) is set to 6, the population size is taken to be 50, the number of iterations is 150, the initial value of the quantum rotation angle is 0.01Π, the probability of learning is 0.05, and the convergence accuracy of the tidal current calculation is 10-5, and the reconstruction result is compared with the following methods, respectively: the Particle Swarm Algorithm (PSO), the Simulated Annealing and Taboo Search Algorithm (SA+TS), Heuristic Algorithm (HA), and Pro Ant Colony Cloning Algorithm (ACO). By running the program, the experimental results of the IEEE33 node system are shown in Table 1. Regardless of the heuristic algorithm, particle swarm algorithm, ACO cloning algorithm, and hybrid algorithm of simulated annealing and forbidden search algorithm, the losses in the network after reconfiguration have been reduced to a great extent, and the lowest node voltage has been significantly improved, and the active network loss in the network before reconfiguration is 203.91kW, and after reconfiguration the active network loss is 138.84kW, which is a reduction of the active network loss by 65.07 kW, a decrease of 31.91%, and the minimum node voltage before and after reconfiguration is increased from 0.9139 p.u. to 0.9421 p.u.. The extensive learning quantum evolution algorithm is also able to search the same optimal solution, which verifies the effectiveness and feasibility of the algorithm. Fig. 8 represents the network loss convergence when reconfiguration is utilized with CLQIEA, and the algorithm runs up to the 10th generation to search for the optimal solution. Figure 9 shows the node voltage distribution before and after reconfiguration, which shows that the system node voltage is significantly improved, and the overall voltage is improved by 1.95% after reconfiguration.

Table 1. Experimental results of the IEEE33 node system

Test system	Method	Open switch	Work network loss/kW	Minimum node voltage/p.u.
IEEE33	Before refactoring	33,34,35,36,37	203.91	0.9139
	HA	7,9,14,32,37	138.84	0.9421
	SA+TS	7,9,14,32,37	138.84	0.9421
	PSO	7,9,14,32,37	138.84	0.9421
	ACO	7,9,14,32,37	138.84	0.9421
	CLQIEA	7,9,14,32,37	138.84	0.9421

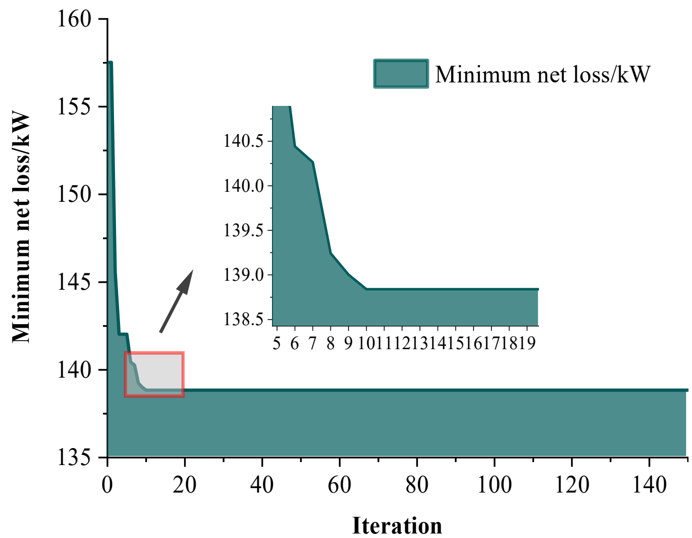

Fig. 8. The net loss convergence when the CLQIEA is reconstructed(IEEE33)

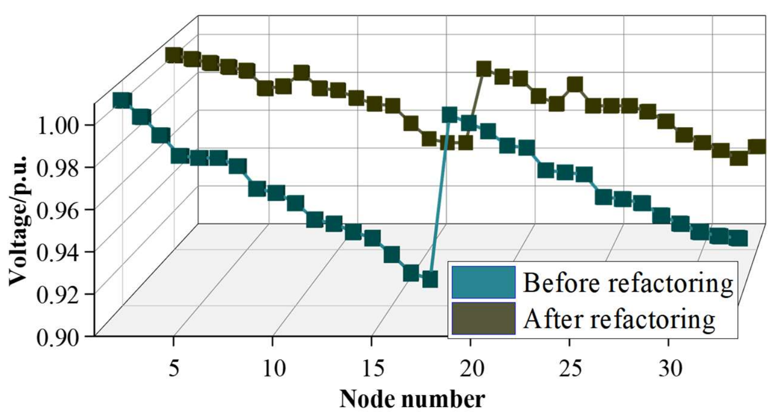

Fig. 9. The node voltage distribution before and after the reconstruction(IEEE33)

4.2.2. PG&E69 Node System. The PG&E 69 node system has 69 nodes, 68 sectional switches, and 5 contact switches, the rated voltage of the system is 12.66 kV, the total active power is 3802.19 kW, and the total reactive power is 2694.60 kW. the initial contact switches are 69, 70, 71, 72, and 73, including 5 rings.

The parameter settings are the same as in the previous section, and the results of the reconfiguration are compared with the following methods, respectively: the Improved Immunogenetic Algorithm (IIGA), the Ant Colony Algorithm (ACS), the Hybrid Differential Evolutionary Algorithm (VSHDE), and the Hybrid Particle Swarm Algorithm (HPSO). By running the program, the experimental results of the PG&E 69-node system are shown in Table 2. The extensive learning quantum evolution algorithm is able to search the optimal solution better than the other algorithms, the active network loss in the network before reconfiguration is 226.564kW, and after reconfiguration the active network loss is 99.433kW, which reduces the active network loss by 127.131kW, which is a decrease of 56.11%, and the minimum node voltage before and after reconfiguration increases from 0.9091p.u. improved to 0.9446p.u.. The results show that the network loss is significantly reduced and the minimum node voltage is significantly improved, which once again verifies the effectiveness and feasibility of the CLQIEA algorithm in this paper and achieves a better reconfiguration effect. Figure 10 represents the network loss convergence when using CLQIEA reconfiguration, and the algorithm runs to the 13th generation that searches for the optimal solution. Fig. 11 shows the distribution of node voltages before and after reconfiguration, and the mean value of the system voltages at each node after reconfiguration increases from 0.974 to 0.986, which is an increase of 1.23%.

It can be seen that the distribution system reconfiguration based on CLQIEA in this paper can largely reduce the network loss and improve the voltage quality of the system, which is conducive to the economic operation of the system.

Table 2. Experimental results of the PG&E69 node system

Test system	Method	Open switch	Work network loss/kW	Minimum node voltage/p.u.
IEEE33	Before refactoring	69, 70, 71, 72, 73	226.564	0.9091
	IIGA	69,14,70,47,50	99.632	0.9325
	ACS	61,69,14,70,55	99.551	0.9431
	VSHDE	11,24,28,43,56	99.627	0.9429
	HPSO	69,12,14,47,50	99.707	0.9428
	CLQIEA	47,12,50,14,69	99.433	0.9446

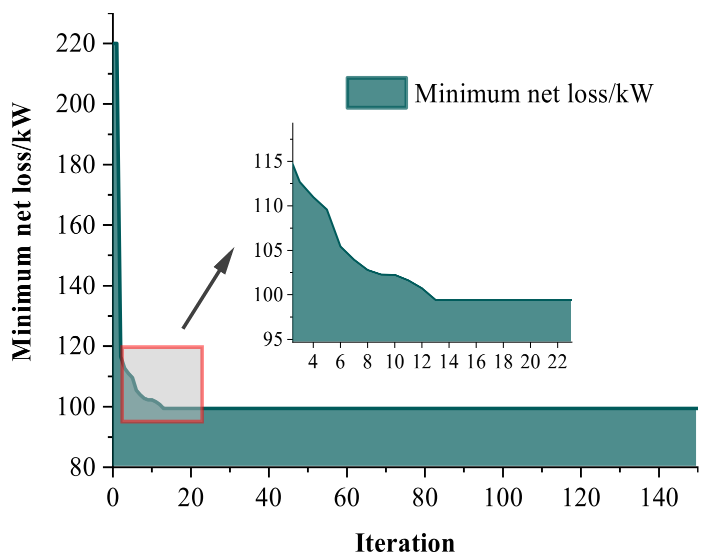

Fig. 10. The net loss convergence when the CLQIEA is reconstructed(PG&E69)

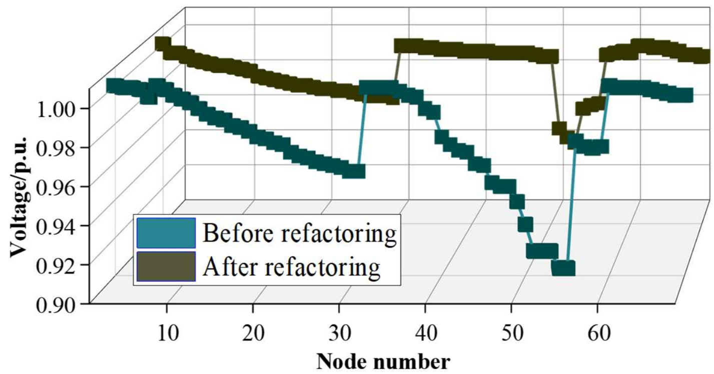

Fig. 11. The node voltage distribution before and after the reconstruction(PG&E69)

5. Conclusion

As the development of electronic power distribution system automation is emphasized, more and more accurate and reliable distribution system operation data can be utilized to integrate deep learning methods to identify the real-time topology of the distribution system.This study is based on graph neural network, and realizes the topology identification of the distribution system by constructing a network model. Then the reconfiguration method of the distribution system is proposed by combining the extensive learning quantum evolutionary algorithm to optimize the operation of the distribution system.

1) The F1 results of the GNN model in this paper tested on four different distribution systems are 0.913~0.961, which are improved by 5.64%~29.64% over other topology identification methods. It can reduce the influence of noise data on topology identification, and the identification accuracy averages 0.921 in several modified IEEE33 systems, which shows good accuracy and robustness, and has some value for engineering applications.

2) In the experiments of IEEE33 and PG&E 69-node systems, the active network loss decreases by 31.91% and 56.11%, and the minimum node voltage improves by 3.09% and 3.90%, respectively, after applying the CLQIEA method for reconfiguration. In addition, the network losses under the application of CLQIEA method converge faster, and the average voltage values at each node of the two systems increase by 1.95% and 1.23% after reconfiguration. The CLQIEA-based reconfiguration scheme in this paper can reduce the network losses to a larger extent and improve and enhance the power quality of the system.

In this paper, topology identification and reconfiguration of electronic power distribution systems have been studied with some success, but there are still many shortcomings. The arithmetic examples in this paper do not fully consider the future load changes of the distribution system. The continuous access of distributed new energy sources, energy storage, and electric vehicles increases the complexity of the distribution system topology, and the impact on the topology identification of the distribution system needs to be further studied.

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