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Fault Analysis Method of Active Distribution Network Under Cloud Edge Architecture

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ABSTRACT

Efficient fault treatment of active distribution network is an important guarantee to ensure the steady-state reliability of the system. In order to improve the accuracy of distribution network fault identification and analysis, a fault processing method based on deep learning is proposed in this paper. This method collects massive heterogeneous data sets using patrol robot to realize real-time perception and accurate acquisition of distribution network status. Relying on the processing mode of distribution network cloud edge collaboration, the principal component analysis method is used at the edge to effectively remove redundant data, providing a complete and reliable data support for the deep network model. Meanwhile, the attention mechanism is added to the cloud to improve the depth confidence network, further realizing the extraction of useful feature information for complex data sets and avoiding the interference of irrelevant information on the recognition results. The simulation experiment is based on the actual active distribution network model. The experimental results show that the fault identification accuracy Acc of the proposed method can reach 0.9255, indicating an excellent distribution network fault identification and analysis ability to support safe operation of active distribution network.

KEYWORDS

Active Distribution Network, Attention Mechanism, Cloud Edge Collaboration, Deep Belief Network, Fault Analysis, Principal Component Analysis

INTRODUCTION

Efficient and accurate fault identification of distribution network can support the stability and controllability of smart grid (Montakhab, Adams, 1998). With the access of distributed power source, the traditional distribution network has changed from the original radial network to the complex active distribution network with interconnected power sources and users (Tajdinian, et al, 2020). At the

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same time, the applicability and accuracy of traditional distribution network fault location methods are reduced, also bringing difficulties to relay protection (Le, et al, 2020; Chen, et al, 2020).

The distribution network fault is hidden. If the fault line is not cut off in time, it will cause great potential safety hazards. For example, in case of single-phase grounding fault, the line voltage remains symmetrical, but the phase voltage of non-fault phase will increase by three times. At this time, there is a risk of insulation breakdown of power equipment, which may cause two-point or multi-point grounding short-circuit fault, leading to further development of the fault (Liang, et al, 2020; Hagh, et al, 2019; Miguel, 2022). Therefore, the distribution network fault must be identified in time and handled quickly.

The fault treatment of distribution system mainly includes distance fault identification method and matrix algorithm based on Distribution Automation Terminal (Xie, et al, 2020; Gao, et al. 2021; Yao, et al, 2021). Function approximation is used as the basic goal to establish the 0-1 integer optimization model, and then faults are located through optimization algorithm, but there are some problems such as slow calculation speed, difficult construction of function model and poor convergence of optimization algorithm (Jia, et al, 2019; Xu, et al, 2019). It is not enough to cope with the increasingly complex active distribution network.

The emergence of deep learning network provides a new solution to fault identification of active distribution network. Deep neural network is constructed by using massive data training, the characteristics of input data are automatically extracted, and induction and classification are implemented accordingly (Ganjkhani, et al, 2021; Hou, et al, 2022; Zhao, Barati, 2021). At present, many researchers have carried out power grid fault identification and research based on deep network. Luo et al (2019) introduced the automatic encoder into the deep learning network model to realize the fault identification and analysis of radial distribution network; (Sun et al, 2021) proposed an adaptive long short memory network regression model to realize the state detection and fault identification of power transmission network by establishing the corresponding relationship between similar time factors and long and short-term memory network (LSTM). Based on the high-voltage direct current high voltage direct current system (HVDC), Wang, He and Li (2021) optimized convolutional neural network (CNN) and LSTM network models to realize fault identification and judgment of transmission lines; Rai, Londhe and Raj (2020) focused on the scene of active distribution network, and used CNN to build a fault identification model to support its safe operation. Based on the convolutional neural network (CNN), Zhang et al (2022) constructed a network structure fully suitable for power grid fault diagnosis, and took the minimum cross entropy as the goal to mine the deep fault features to achieve the fault diagnosis analysis of AC/DC transmission system. Wei et al (2021) used two bidirectional short-term and short-term memory networks as the basic classifiers, and applied the cross-entropy loss function and cost-sensitive loss function to the two classifiers respectively, effectively reducing the impact of sample category imbalance in fault event recognition. Yan et al (2022) input the word vector into the CNN deep learning model for training, and introduce the DSA mechanism to improve the CNN model according to the characteristics of the power grid alarm information.

However, it should be noted that the distribution network are characterized with terminal heterogeneity and high-dimensional data. Although the above method migrates the deep learning network to the power grid fault identification and analysis, it does not solve the problem of high-dimensional and redundant distribution network data sets (Barrios, et al, 2021; Ceci, et al, 2020), which will make the multi-layer network fall into the problem of local optimization in data analysis or even the problem of solution divergence, thus resulting in the low analysis efficiency.

For the modern distribution system, a fault identification method based on deep learning and cloud edge cooperation mode is proposed. The main innovations of this method are as follows:

1. Using intelligent equipment such as patrol robot at distribution network terminals, complete and original distribution network sample data sets are built for typical places such as switchyards and ring network cabinets to realize accurate perception of distribution network status;

2. Based on the principal component analysis (PCA), the collected state data is optimized at the edge of the network, the original features of the data collected by the distribution network are reduced to lower the redundancy of data samples, improve the reliability and interactivity of the input data of the fault identification model, and provide a reliable and complete training sample data set for the cloud analysis model;
3. In the distribution network cloud, the attention mechanism (AM) is used to optimize the deep belief network (DBN) model and build the attention mechanism deep belief network (AM-DBN) active distribution network fault identification model, which can more accurately obtain the deep effective information in complex data samples and achieve efficient and accurate analysis of distribution network faults.

CLOUD EDGE COLLABORATION ARCHITECTURE

Introducing cloud edge collaboration architecture into active distribution network can complete complex and huge computing tasks with higher efficiency and lower cost (Zhang, et al, 2021). The proposed fault identification scheme of active distribution network is realized by the improved DBN network model.

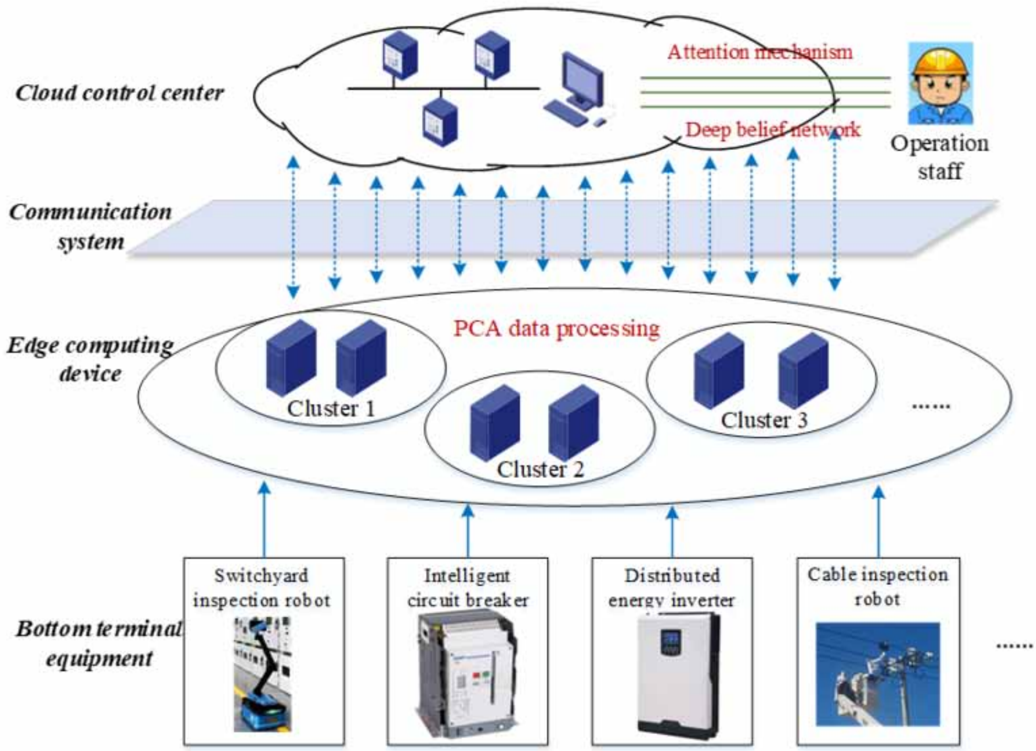
Cloud edge collaboration mode is an efficient computing mode that combines cloud computing mode and edge computing mode. It can achieve efficient pre-processing operations for network collected data at the edge of the network by virtue of the advantages of edge computing devices, such as real-time and lightweight computing. On the cloud platform side of the network, we use artificial intelligence technology, big data storage and analysis technology to analyze and process data, so as to achieve accurate perception and control of network status (Logeswaran, 2021; Sridharan, Domnic, 2021; Zhang, 2021).

The training process of the model is completed in the cloud control center. When the training is completed, the model is distributed to the edge computing equipment to realize local fault identification. For the fault identification and analysis function, the edge side uploads the preprocessed status data to the cloud through the communication system, and realizes training and learning with the help of multi-layer network structure. Figure 1 shows the proposed cloud edge collaboration architecture of active distribution network.

The structure of each layer in Figure 1 is as follows:

1. Bottom terminal equipment: the intelligent robot terminal close to the user in the marketing power distribution link can collect real-time information of typical places such as switch stations and ring main cabinets, and also respond to control instructions issued by edge computing equipment or distribution network cloud control center.
2. Edge computing equipment: an edge node with data storage, calculation and analysis capabilities is set between the distribution network cloud control center and the underlying terminal equipment. It preprocesses the collected state data of the bottom terminal equipment and uploads it to the cloud control center of the distribution network to support various advanced application scenarios at the top, such as network status awareness, line loss analysis, load forecasting, fault location and other functional applications.
3. Cloud control center: as the decision-making center of distribution network, it uses the multilayer network model to analyze and process data on the cloud platform to realize fine regulation of terminal equipment. For the fault identification architecture, in the cloud center, attention mechanism (AM) can be used to optimize the deep trust network (DBN) model to obtain deep and effective information in complex data samples.
4. Pipeline communication system: the communication network between the underlying power distribution internet of things (IOT) terminal and the edge computing equipment, and between the edge computing equipment and the cloud control center. It is mainly used to transmit the

Figure 1.
Cloud edge collaboration architecture for fault identification



status data collected by the bottom terminal, the data after calculation and procession by the edge computing equipment and the data sent by the cloud control center.

FAULT IDENTIFICATION METHOD BASED ON DEEP LEARNING

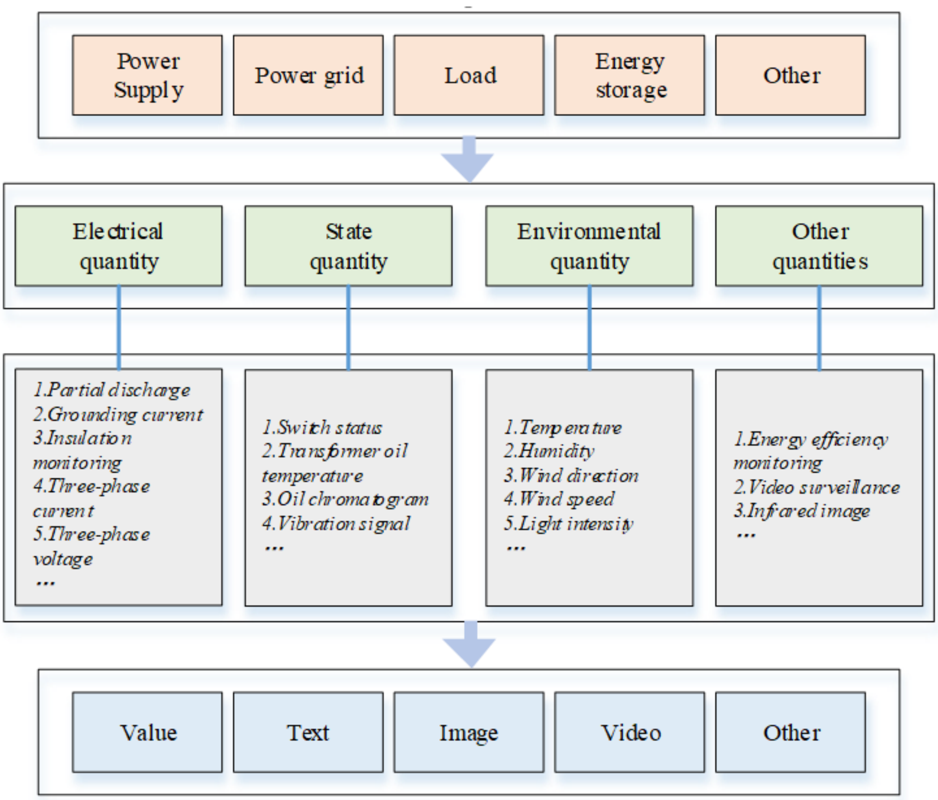
Distribution Network Situation Perception

In order to realize holographic panorama perception of distribution network, this paper uses patrol robot at the bottom of the network to obtain multi-source heterogeneous data sets in typical places such as switch stations and ring network cabinets. The distribution network status data set is shown in Figure 2.

The perception types of the inspection robot can be divided into electrical quantity, state quantity, environment quantity and other quantities. Electric quantity is obtained by using electromagnetic sensors and other sensing equipment, including current, voltage and other data of electric equipment. The state quantity mainly refers to the operation state monitoring data of switchgear, transformer and other equipment. The environmental quantity is obtained by using the locally deployed micro meteorological sensing device, including the temperature, humidity, light intensity and other data within the local range. Other quantities include the action and behavior data of the actors involved in the operation of the distribution network obtained by cameras, operation logs, etc.

The perception format of the inspection robot is different and can be divided into numerical data, text data, vibration data, image and video data, mixed data and multi-source heterogeneous data. The intelligent perception of complex equipment usually requires multiple inspection robots to collect

Figure 2.
Data set collected by patrol robot



multiple types of multi-source heterogeneous data at different angles and levels. For example, the intelligent perception of transformer requires not only the perception of its electrical parameters such as current and voltage, but also the perception of its oil chromatography, gas composition, infrared image, etc., so as to better analyze the transformer status and fault.

PCA Data Preprocessing

With the rapid construction and development of the power grid, the equipment data, operation data and other relevant network data of the distribution network are characterized by large scale and complex data structures. Moreover, the data involves multiple applications and systems of the power grid company, and there are a lot of redundancy and inconsistency between the data, which is not conducive to the accurate and efficient fault identification and location of the distribution network. In order to solve this problem, we use principal component analysis to preprocess the distribution state data at the edge of the distribution network (Feng RN, et al, 2021).

The purpose of using PCA technology is to reduce the redundancy of the original collected data, so as to eliminate the dimension disaster caused by data complexity on model data analysis (Shu, et al, 2020; Li, et al, 2021).

The technical operation of PCA mainly takes four steps:

(Data Standardization): Considering that the value ranges of the input data component $\left\{s_1, s_2, \&, s_z\right\}$ may be inconsistent, the input data (1) is first standardized with formula (2)

$$[S_1, S_2, \ \ldots, S_Z]^T = \begin{bmatrix} s_{11} & s_{12} & \cdots & s_{1y} \\ s_{21} & s_{22} & \cdots & s_{2y} \\ \vdots & \vdots & \vdots & \vdots \\ s_{z1} & s_{z2} & \cdots & s_{zy} \end{bmatrix} \tag{1}$$

$$\tilde{s}_{zy} = \frac{s_{zy} - \overline{s}_z}{r_z} \tag{2}$$

where, z is the number of data types collected by the power terminal, y is the number of data samples under each data type, and $\overline{s}_z$ and r_z are calculated from formulas (3) to (4).

$$\overline{s}_z = \frac{\sum_{y=1}^{Y} s_{zy}}{Y} \tag{3}$$

$$r_z = \sqrt{\frac{\sum_{y=1}^{Y} (s_{zy} - \overline{s}_z)^2}{Y - 1}} \tag{4}$$

The original input is converted into a standardized matrix.

$$[\tilde{S}_1, \tilde{S}_2, \ \ldots, \tilde{S}_Z]^T = \begin{bmatrix} \tilde{s}_{11} & \tilde{s}_{12} & \cdots & \tilde{s}_{1y} \\ \tilde{s}_{21} & \tilde{s}_{22} & \cdots & \tilde{s}_{2y} \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{s}_{z1} & \tilde{s}_{z2} & \cdots & \tilde{s}_{zy} \end{bmatrix} \tag{5}$$

(Covariance Matrix Calculation): The covariance matrix of the standardized matrix is calculated according to formulas (6) to (8).

$$\overline{\tilde{s}}_z = \frac{\sum_{y=1}^{Y} \tilde{s}_{zy}}{Y} \tag{6}$$

$$\Gamma = \begin{bmatrix} \tilde{s}_{11} - \overline{\tilde{s}}_1 & \tilde{s}_{12} - \overline{\tilde{s}}_2 & \cdots & \tilde{s}_{1y} - \overline{\tilde{s}}_y \\ \tilde{s}_{21} - \overline{\tilde{s}}_1 & \tilde{s}_{22} - \overline{\tilde{s}}_2 & \cdots & \tilde{s}_{2y} - \overline{\tilde{s}}_y \\ \vdots & \vdots & \vdots & \vdots \\ \tilde{s}_{z1} - \overline{\tilde{s}}_1 & \tilde{s}_{z2} - \overline{\tilde{s}}_2 & \cdots & \tilde{s}_{zy} - \overline{\tilde{s}}_y \end{bmatrix} \tag{7}$$

$$\Sigma = \frac{1}{Z - 1} \Gamma^T \Gamma \tag{8}$$

(Eigenvalue and Eigenvector Calculation): The singular value decomposition is used to solve the eigenvalues and eigenvectors of power state data, and the covariance matrix Σ. The singular values are arranged in order according to the characteristics of the eigenvalues, and the operations are converted.

$$\left| \Sigma - \lambda_y I \right| = 0 \tag{9}$$

$$\Sigma\chi_y = \lambda_y \chi_y \tag{10}$$

where, λ_y is the eigenvalue and χ_y is the unit eigenvector corresponding to the eigenvalue λ_y.
(Contribution Rate Verification and Principal Component Vector Acquisition): The Y' vectors are selected before the cumulative principal component contribution rate exceeds $\eta\%$ to construct new input data.

$$[S_1', S_2', \ldots, S_z']^T = \begin{bmatrix} \chi_{11}(\tilde{s}_{11} - \overline{\tilde{s}}_1)^T & \chi_{12}(\tilde{s}_{12} - \overline{\tilde{s}}_2)^T & \cdots & \chi_{1y'}(\tilde{s}_{1y'} - \overline{\tilde{s}}_{y'})^T \\ \chi_{21}(\tilde{s}_{21} - \overline{\tilde{s}}_1)^T & \chi_{22}(\tilde{s}_{22} - \overline{\tilde{s}}_2)^T & \cdots & \chi_{2y'}(\tilde{s}_{2y'} - \overline{\tilde{s}}_{y'})^T \\ \vdots & \vdots & \vdots & \vdots \\ \chi_{z1}(\tilde{s}_{Z1} - \overline{\tilde{s}}_1)^T & \chi_{z2}(\tilde{s}_{z2} - \overline{\tilde{s}}_2)^T & \cdots & \chi_{zy'}(\tilde{s}_{zy'} - \overline{\tilde{s}}_{y'})^T \end{bmatrix} \tag{11}$$

where, the value of Y' meets the following constraints:

$$\frac{\sum_{y'=1}^{Y'} \lambda_{y'}}{\sum_{y=1}^{Y} \lambda_y} \geq \eta\% \tag{12}$$

where, λ_y is the characteristic value of power state data; η is the cumulative principal component contribution rate of the model.

Thus, the training data samples after PCA preprocessing are S_z' and $(z = 1, 2, \& \&, Z)$, where, the calculation formula of S_z' is:

$$S_z' = [\chi_{z1}(\tilde{s}_{z1} - \overline{\tilde{s}}_1)^T, \chi_{z2}(\tilde{s}_{z2} - \overline{\tilde{s}}_2)^T, \ldots, \chi_{zY'}(\tilde{s}_{zY'} - \overline{\tilde{s}}_{Y'})^T] \tag{13}$$

Fault Identification Model Based on Improved DBN Network Model

Traditional data analysis methods can effectively extract the features of data of low dimension. When the data dimension is too high, the effect of these methods will be significantly reduced (Wu, et al, 2021).

Deep belief network has good ability in data feature extraction and mapping. It can learn from the original data through multi hidden layer network and is suitable for solving complex high-dimensional classification problems (Xing, et al, 2021; Hong JH, et al, 2021). Aiming to better capture the effective data feature information, we introduce the attention mechanism to optimize the DBN network and reduce the attention to irrelevant information. Therefore, the ability to obtain information can be improved, irrelevant factors interfering with the analysis results can be avoided. By building the AM-DBN active distribution network fault identification model, we improve the accuracy of fault classification, and achieve accurate and efficient analysis of distribution network faults.

Deep Belief Network

Different from the typical neural network training method, the deep belief network uses the contrast divergence algorithm to adjust the connection weight and bias layer by layer. The DBN network consists of multiple restricted boltzmann machine (RBM) stacked together. The specific method is to train the parameters between the input layer and the first hidden layer first. Then, the output of the trained RBM1 is used as the input of RBM2 to train the parameters of RBM2, and so on. The unsupervised learning of DBN network is realized by layer-by-layer training, as shown in Figure 3.

DBN network can be used as a generation model or a discrimination model. To realize the fault identification and analysis of active distribution network, which is a typical classification problem, this paper adopts DBN as a discrimination model, and thus a classifier is connected in the hidden layer of the last RBM.

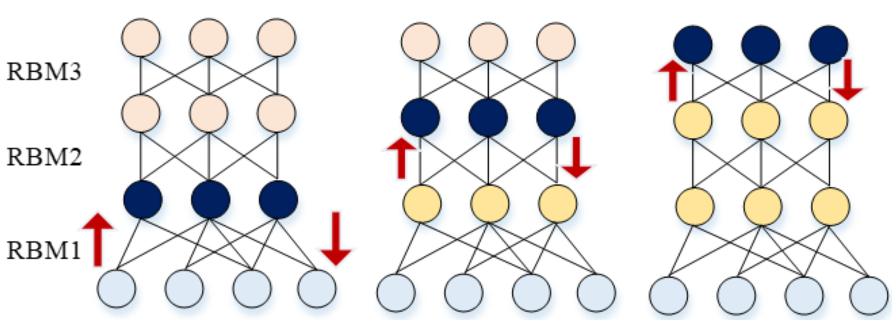
The fault identification in this paper is a multi-classification problem. Therefore, softmax classifier is used for classification, and the features mined by stacking constrained Boltzmann machine are used as the input of softmax, so as to realize the data classification.

In the softmax classifier, it is assumed that the training set has q samples, and these q samples are divided into p classes. The training set can be expressed as $\left\{(s_1,u_1),(s_2,u_2),\ldots,(s_i,u_i),\ldots,(s_z,u_z)\right\}$, $s_i \in R$ represents the i training sample, u represents the category output in the classification problem, and $u_i \in \{1,2,\ldots,p\}$. After the data is input into the model, the data is judged as the category with the largest probability value by calculating the probability of belonging to each category. Here, the probability value of a given test set data s belonging to a certain class is $P(u=e|s)$. Since there are p classes, the probability value of s belonging to each class can be expressed by p dimension vector. The function for calculating the probability value is as follows:

$$v_\lambda(s_i)=\begin{bmatrix} P(u_i=1|s_i;\lambda) \\ P(u_i=2|s_i;\lambda) \\ \vdots \\ P(u_i=p|s_i;\lambda) \end{bmatrix}=\frac{1}{\sum_{c=1}^{p} e^{\lambda_c^T s_i}}\begin{bmatrix} e^{\lambda_1^T s_i} \\ e^{\lambda_2^T s_i} \\ \vdots \\ e^{\lambda_p^T s_i} \end{bmatrix} \tag{14}$$

where, the vector of each dimension of $v_\lambda(s_i)$ vector represents the probability that the fault belongs to different types of faults. Here, since the fault must belong to one of them, the sum of each column of the probability matrix is 1, so $\frac{1}{\sum_{c=1}^{p} e^{\lambda_c^T s_i}}$ is used to normalize the matrix, where $\lambda_1,\lambda_2,\ldots,\lambda_p \in R$

Figure 3.
DBN training process



represents the network parameters of softmax model. The cross entropy loss function used by softmax classifier is as follows:

$$Loss = \frac{1}{q}\sum_{e=1}^{q}\sum_{i=1}^{p} t_{ie} \ln u_{ie} + (1 - t_{ie})\ln(1 - u_{ie}) \tag{15}$$

where, q represents the number of data samples, p represents the number of categories, u_{ie} represents the output of the network when the input sample is s_i, and t_{ie} represents the target output category of the i sample.

By training softmax, the optimal parameter λ of the network is obtained. The trained softmax classifier is used to classify the data. The probability value of a category output by the network is the largest, and the sample belongs to that category.

In this paper, the softmax layer is connected to the last layer of the stacking constrained Boltzmann machine, and the other layers are trained with the contrast divergence algorithm, and then the trained parameters are used as the initial value of network fine-tuning.

In the fine-tuning process, the labeled training set data is used to optimize the parameters of the entire DBN network by adopting the back propagation algorithm, and the chain derivative algorithm is used to calculate the partial derivative of the loss function between the actual output result and the ideal result to each weight parameter or offset term. Then, according to the optimization algorithm, the weight or bias term is updated layer by layer in reverse. By constantly adjusting the parameters in the model, the loss function converges and better network parameters are obtained.

AM-DBN Model

Aiming to further support the recognition performance of the state analysis network model, we introduce attention mechanism to optimize DBN model and reduce the attention to irrelevant information. (Guo, et al, 2021).

In the extracted sample data matrix $\left\{s_1, s_2, \&, s_z\right\}$, the attention mechanism optimization is introduced and transformed into the hidden layer feature $\left\{s_1', s_2', \&, s_z'\right\}$. The attention matrix can be calculated by equations (16-18).

$$\alpha_i = \tanh(w_\alpha s_i' + \beta_i) \tag{16}$$

$$\theta_i = \frac{e^{A_i}}{\sum_{i=1} e^{A_i}} \tag{17}$$

$$\varphi = \sum_{i=1} \theta_i s_i' \tag{18}$$

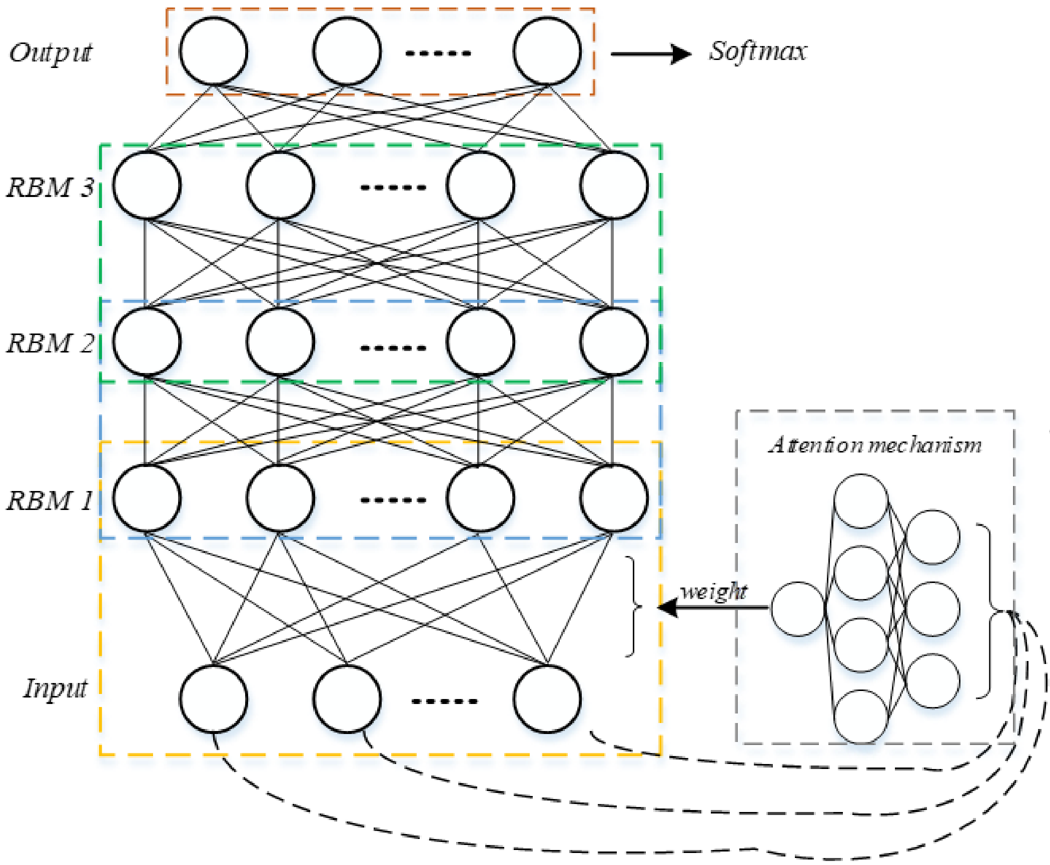
where θ_i is the weight parameter, and w_α is the weight matrix. Finally, the characteristic expression is obtained by summing the series of equation (18).

In the training and learning process of AM-DBN, the features extracted by DBN network are weighted by the time dimension of attention mechanism to highlight the main features and ignore the secondary features to achieve more accurate fault classification.

Figure 4 is the fault identification model of AM-DBN active distribution network proposed in this paper.

As shown in Figure 4, the AM-DBN fault detection network converts the features extracted by the DBN network into hidden layer features by giving the time dimension of the attention mechanism

Figure 4.
AM-DBN fault identification network model



weighting, highlights the main features and ignores the secondary features, so as to achieve more accurate fault classification.

EXPERIMENT AND ANALYSIS

Single-phase grounding fault is a common operation fault of power grid. This paper will carry out corresponding research and analysis based on it.

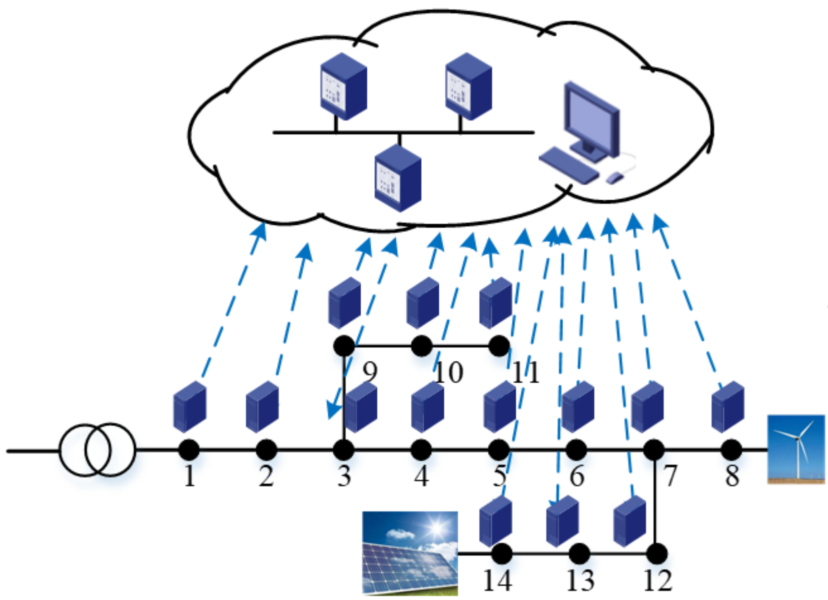
In order to present the experimental simulation analysis with the best effect, the improved DBN network model proposed in this paper is implemented by Python script and uses tensorflow framework. The deep learning algorithm runs in pycharm software. The main configuration of the experimental environment is shown in Table 1.

The experimental calculation takes a 10.5 kV distribution network in a province in eastern China as an example. The active distribution network has four branches, as shown in Figure 5. Each node has edge computing capacity. At the end of the upper and short branches, there are distributed power stations dominated by wind power generation and photovoltaic power generation, in which the installed capacity of wind power is 2.5 MVA and the installed capacity of photovoltaic power is 2.0 MVA.

Table1.
Parameter setting of experimental analysis platform

Project	Parameter
Operating System	Ubuntu 18.04
CPU	Inter(R) Core(TM) i7-10875H
GPU	GeForce RTX 2060 TI
RAM	16 GB
Development language	Python
Development platform	Pytorch
Development tool	Pycharm

Figure 5.
Branch structure of active distribution network



Evaluating Indicator

When evaluating the performance of the fault identification method, the confusion matrix method is adopted. T_P determines the actual fault as a positive example, T_N determines the actual failure as a negative example, F_P determines the actual failure as a positive example, and F_N determines the actual failure as a negative example. It can be represented by the confusion matrix in Table 2 below.

Four indicators are usually used to judge the performance of AM-DBN network model, namely accuracy Acc, precision Pre, detection rate Re, and false positive rate F_1. It should be noted that for these four indicators, the higher the value, the better the detection performance.

$$Acc = \frac{\left|T_P\right| + \left|T_N\right|}{\left|T_P\right| + \left|F_P\right| + \left|T_N\right| + \left|F_N\right|} \tag{19}$$

Table 2.
Confusion matrix

	True	False
True	T_P	T_N
False	F_P	F_N

$$Pre = \frac{\left|T_P\right|}{\left|T_P\right| + \left|F_P\right|} \tag{20}$$

$$Re = \frac{\left|T_P\right|}{\left|T_P\right| + \left|F_N\right|} \tag{21}$$

$$F_1 = 2 \times \frac{Pre \times Re}{Pre + Re} \tag{22}$$

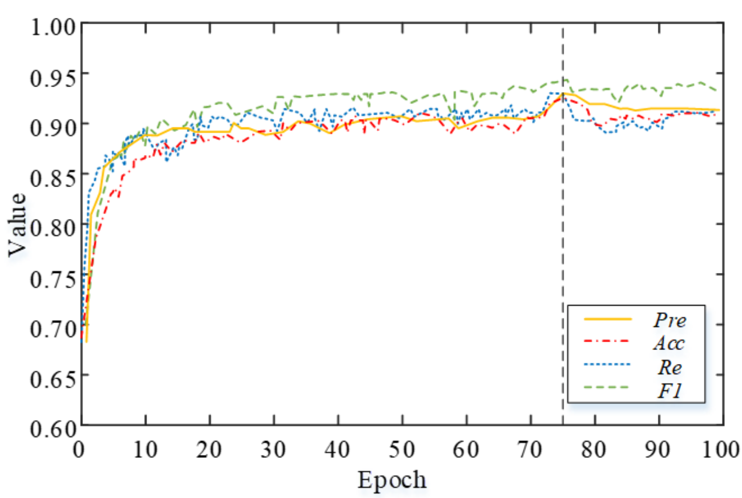
Training Process

The initial input data dimension of the simulation example is 16. The traffic flow in the input data adopts the effective value, while the value of the input data adopts the mean value of the sampling value within 20 ms before and after the fault.

The input data of each type of fault is generated by sampling after randomly selecting the location and number of distribution network fault nodes. Each type of fault runs 1500 times to form a data set, and 80% is randomly selected as the training sample.

The AM-DBN fault identification network model constructed in this paper is used for model learning in the training data set. During the training and testing of 100 epochs, the change process of accuracy Acc, precision Pre, detection rate Re and false positive rate F_1 is shown in Figure 6.

Figure 6.
Model training and testing process



From Figure 6, it can be concluded that the performance of the proposed model reaches the best in 75 epoch fault identification models, and the evaluation indexes of the four types of models reach the best, with Acc of 0.9255, Pre of 0.9264, Re of 0.9261 and F_1 of 0.9411. It is confirmed that the AM-DBN model can accurately and efficiently identify and analyze the faults of active distribution network. The reason is that this paper uses AM mechanism to further enhance the ability of DBN model for data feature mining. At the same time, the application of back-propagation algorithm also makes the construction of fault discrimination model more accurate.

Experimental Demonstration

Aiming to illustrate the advantages of the AM-DBN model, LSTM (Sun H, et al, 2021) and CNN (Rai P, et al, 2020) are used as comparison methods, and experimental simulation analysis is carried out based on the test sample data set. The comparison methods all run under the same operating environment.

The identification results and performance comparison of different fault identification methods are shown in Figure 7.

As shown in Figure 7, the AM-DBN model can accurately identify complex distribution network faults. The recognition accuracy and precision are 0.9262 and 0.9231, respectively, 0.0242 and 0.0231 higher than that used by CNN.

The reason is that the proposed AM-DBN based active distribution network fault identification method introduces PCA technology to effectively improve the completeness and reliability of sample data sets. At the same time, the introduction of AM mechanism enables the fault identification network model to accurately obtain the effective feature information in the sample data set and reduce the influence of irrelevant information on the recognition results.

Meanwhile, we study the efficiency of model analysis. Table 3 shows the fault identification sensitivity of different methods.

It can be seen from Table 3 that the AM-DBN model can realize fault state identification and diagnosis in 0.125s, which is 0.09s and 0.16s shorter than LSTM and CNN, respectively. This is also the advantage of adopting cloud edge collaboration mode, which can realize the rapid perception and analysis of complex power grid state.

Figure 7.
Distribution network fault identification performance of different methods

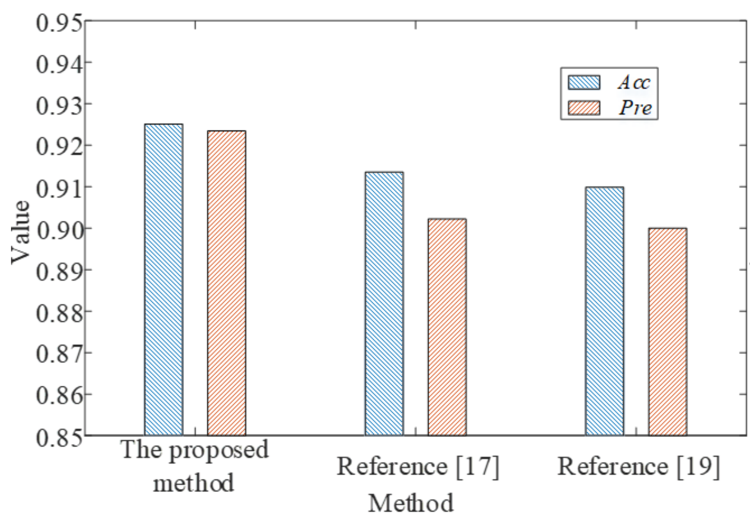


Table 3.
Time consumption of different fault identification methods

Method	Time (s)	Acc
The proposed method	0.125	0.9262
LSTM	0.134	0.9142
CNN	0.141	0.9020

In terms of the comprehensive recognition accuracy and model efficiency, the proposed AM-DBN model has the best performance, and can meet the requirements of accurate and fast fault identification and support the reliable and safe operation.

CONCLUSION

The emergence of deep learning model provides a good solution for the abnormal state of active distribution network. Based on the cloud edge collaborative processing model, this paper proposes a fault identification method using improved DBN model. This method completes situation perception, data preprocessing and analysis model building in the cloud edge end of distribution network. The introduction of patrol robot can realize massive and reliable acquisition of multi-source heterogeneous data of distribution network; The application of PCA technology can realize reliable data dimensionality reduction and optimization processing at the edge of distribution network, and improve the quality of data used in the model; The addition of attention mechanism improves the capability of obtaining feature information of DBN model, further ensuring that the proposed method can achieve efficient and accurate fault identification and analysis. Simulation results show that the proposed method can provide reliable and timely operation guarantee for the actual complex active distribution network.

Although the method proposed has excellent fault identification ability, its model parameters are fixed values, which is difficult to adjust automatically according to the data characteristic information. The next research work is to introduce parameter adaptive algorithm into the model to enhance the ability of parameter optimization and further improve the efficiency of fault identification methods.

DATA AVAILABILITY

The data is available from the corresponding author.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

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