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Deep Learning-based Intelligent Fault Diagnosis for Power Distribution Networks

J.Z. Liu, Q.L. Qu, H.Y. Yang, J.M. Zhang, Z.D. Liu

Jingzhi Liu*
State Grid Qinghai Electric Power Company Electric Power Research Institute
Xining, Qinghai, 810008, China
*Corresponding author: g002@zitonginfo.com

Quanlei Qu
State Grid Qinghai Electric Power Company Electric Power Research Institute
Xining, Qinghai, 810008, China

Hongyi Yang
State Grid Qinghai Electric Power Company Electric Power Research Institute
Xining, Qinghai, 810008, China

Jianming Zhang
State Grid Qinghai Electric Power Company Electric Power Research Institute
Xining, Qinghai, 810008, China

Zhidong Liu
State Grid Qinghai Electric Power Company Electric Power Research Institute
Xining, Qinghai, 810008, China

Abstract

Power distribution networks with distributed generation (DG) face challenges in fault diagnosis due to the high uncertainty, randomness, and complexity introduced by DG integration. This study proposes a two-stage approach for fault location and identification in distribution networks with DG. First, an improved bald eagle search algorithm combined with the Dijkstra algorithm (D-IBES) is developed for fault location. Second, a fusion deep residual shrinkage network (FDRSN) is integrated with IBES and support vector machine (SVM) to form the FDRSN-IBS-SVM model for fault identification. Experimental results showed that the D-IBES algorithm achieved a CPU loss rate of 0.54% and an average time consumption of 1.70 seconds in complex scenarios, outperforming the original IBES algorithm. The FDRSN-IBS-SVM model attained high fault identification accuracy (99.05% and 98.54%) under different DG output power levels and maintained robustness (97.89% accuracy and 97.54% recall) under 5% Gaussian white noise. The proposed approach demonstrates superior performance compared to existing methods and provides a promising solution for intelligent fault diagnosis in modern distribution networks.

Keywords: Distributed power supply; Distribution network; Condor search algorithm; Deep residual network; Residual shrinkage module.

1 Introduction

As the end of the power system, the distribution network is responsible for transmitting electric energy from high-voltage transmission lines to user terminals, and plays an important role in connecting power sources and loads. The proportion of distributed generation (DG) in the power system continues to increase as the power system expands and the dual-carbon goal advances [1]. At the same time, the access of DG also brings new challenges to the operation and maintenance of the distribution network. Different types of DG have different operating characteristics and failure modes, which places higher requirements on fault diagnosis algorithms. For example, the fault characteristics of wind power generation systems may be affected by wind speed and temperature, while the faults of solar power generation systems may be related to weather conditions and equipment aging [2]. Various types of DG networks are associated with distinct fault categories, and faults can have an impact on distribution networks while distribution networks can also affect faults. Therefore, fault diagnosis algorithms need to be able to identify and adapt to these diverse fault characteristics. To accurately identify these fault characteristics, many scholars have analyzed fault diagnosis methods. To diagnose gearbox faults more accurately, Yu et al. proposed a feature extraction method based on one-dimensional residual convolution auto-encoder. By introducing a new deep neural network (DNN), fault features were learned from vibration signals in an unsupervised learning manner, and ultimately showed better performance in feature extraction [3]. Zhao et al. proposed a fault diagnosis method that combines graph convolutional networks and deep belief networks to diagnose electromechanical system faults. The objective function was reconstructed under the deep learning framework, and experiments verified that this method has a high diagnostic accuracy [4]. Most scholars focus on diagnosing and analyzing electromechanical or mechanical faults, while few conduct research on distribution network faults. Traditional distribution network faults rely on signal processing technology and empirical rules, which often lack sufficient data processing capabilities. This makes it difficult to quickly and accurately identify faults from a large amount of real-time data [5]. In addition, the large-scale access of DG devices also has high randomness and volatility, which increases the complexity of distribution network fault mechanisms and makes it difficult to locate and identify distribution network faults. The D-IBES algorithm, which combines the Dijkstra algorithm with the improved bald eagle search (IBES) algorithm, is a deep intelligent algorithm that optimizes the solution to the problem by simulating the social behavior of vultures [6]. The algorithm can effectively explore and utilize information in complex search spaces and can be used to deal with complex fault modes in distribution networks [7]. The combination of the fusion deep residual shrinkage network (FDRSN) with IBES and support vector machine (SVM) results in the FDRSN-IBS-SVM model. This comprehensive model utilizes fuzzy logic to process various deterministic and incomplete information, enhancing the adaptability and robustness of the algorithm to DG fault characteristics. As a result, the overall performance of intelligent diagnosis of distribution network faults is improved [8]. To accurately identify and locate distribution network faults, this study proposes an innovative fault diagnosis method based on improved deep learning. The method is designed to diagnose and locate distribution network faults containing DG, with the aim of promoting the safe operation of the distribution network.

The main contributions of the research can be divided into two points. First, the proposed algorithm can effectively identify and process fault characteristics caused by different energy types, improving the accuracy and applicability of diagnosis in view of the complexity of fault characteristics of DG network. Second, through verification, the algorithm is superior to other existing methods in terms of speed and accuracy of fault detection, especially showing significant advantages in processing large-scale data and real-time diagnosis.

2 Related works

With the progress of science, many high-tech technologies have been applied to the field of distribution networks. Zhang's team proposed a fast fault location and isolation method for distribution networks based on adaptive re-closure to address the issues of long fault handling time in existing voltage time feeder automation solutions. Comparative experimental analysis showed that this method could avoid secondary impacts on upstream switches and power outages in the upstream section when permanent faults occur, effectively shortening fault handling time [9]. Chen et al. proposed a single-phase grounding fault location method based on equivalent admittance distortion rate for distribution networks to address the difficulty of locating single-phase grounding faults. This method was simple to perform and had strong robustness against high grounding resistance, long grounding distance, and interference harmonics [10]. Khani et al. proposed an improved fuzzy analytic hierarchy process combined with constrained nonlinear optimization model to address the difficulty and high cost of fault detection and location in distribution overhead line networks. This optimization model could reduce the difficulty of fault localization and is feasible [11]. Mohajer et al. proposed a new distributed generator distribution network fault localization method to address the issue of high-frequency current affecting fault localization in distribution networks. The effectiveness and high efficiency and accuracy of this method had been verified under different fault conditions [12].

To ensure the reliability and safety of distribution network operation, it is not only necessary to locate its faults, but also important to identify the distribution network. Therefore, many scholars have conducted corresponding research. Among them, Liao et al. proposed a fault diagnosis method based on a graph convolutional neural network to improve the accuracy of transformer fault diagnosis. The training process of the method was completed using backpropagation. The results indicated that the algorithm could meet the requirements for fault diagnosis [13]. Zou's team proposed a dual convolutional neural network based transient fault record data recognition model for distribution networks to address the low efficiency of traditional methods in identifying fault types. The recognition accuracy of this model was higher than that of traditional methods [14]. Hosseini et al. proposed a data mining method based on machine learning to address the challenging and time-consuming tasks of phase recognition and power grid rebalancing. It could effectively perform phase recognition in both small and large networks, complete and incomplete data scenarios [15]. To effectively identify rotor bearing system faults, scholars such as Shao proposed a diagnostic method based on fusion of migration blood deficiency and convolutional neural networks. Infrared thermal images were collected during the bearing rotation process to assess its health. The results showed that the diagnostic efficiency of the proposed method was significantly higher [16].

To sum up, existing fault diagnosis methods have faster calculation speed and are easy to implement when dealing with simple and known mode faults. It has good recognition ability for complex failure modes, especially in feature extraction and data recognition. However, when processing fault data, a large amount of annotated data is often required for training, and the model's interpretability is poor. In modern society, there is an increasing demand for electricity, and users are paying more attention to the distribution network. Therefore, the location and identification of distribution network faults are of utmost importance. At present, there are few studies on applying machine learning and deep learning algorithms to identify and locate faults in distribution networks. Therefore, the study proposes a D-IBES model that integrates the Dijkstra algorithm and the IBES algorithm to deal with the problem of fault location in distribution networks with DG, enhancing the algorithm's capability to detect intricate fault modes. Through the powerful feature learning ability of deep learning, it can achieve accurate diagnosis of faults.

3 Research method

3.1 Design of D-IBES Fault Location Algorithm

Due to technological advancements, a significant number of DG devices, such as photovoltaic and wind energy systems, are now connected to the power grid. The traditional power distribution system has been transformed into an active distribution network system with controllable load, energy storage, demand side management, and other capabilities [17]. DG device refers to a small modular independent power supply with a power range of several kilowatts to fifty megawatts, which is compatible with the surrounding environment. The typical structural distribution of the DG device is shown in Figure 1 [18].

The DG device in Figure 1 is mainly divided into fans, photovoltaic panels, batteries, external systems, and other distributed power sources. Due to the integration of DG devices, there is a high

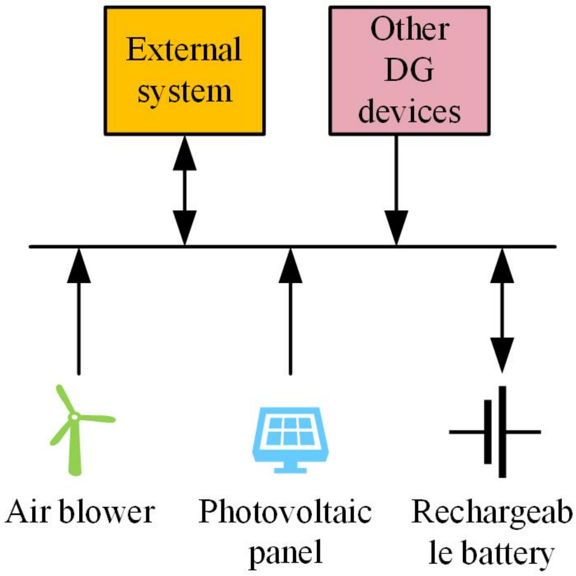

Figure 1: A Schematic diagram of the typical structure of the DG device

degree of uncertainty, randomness, and complexity in the fault characteristics of distribution networks, which also increases the difficulty of fault diagnosis. In response to the above issues, this study uses the bald eagle search (BES) algorithm to partition and locate faults in large-scale distribution networks with DG. The BES algorithm is a new meta heuristic algorithm, inspired by the search behavior of bald eagles (BE) hunting fish, and has strong global search ability. The process of solving the BES can be segmented into selecting search space, search stage, and diving to capture prey. The behavior mathematical model for selecting a search space is described in equation (1).

$$P_{i,new} = P_{best} + 1.5\delta(P_{mean} - P_i) \tag{1}$$

In equation (1), the value range of δ is (0,1) .P_i and P_{mean} respectively are the $i-th$ BE position and the average distribution position after the previous stage of search. P_{best} is the best hunting location for BE in the current space. $P_{i,new}$ is the position of the $i-th$ BE after the update. During the search phase, the BE will move in a spiral shape within the optimal search space to search for the optimal hunting location, as shown in Figure 2.

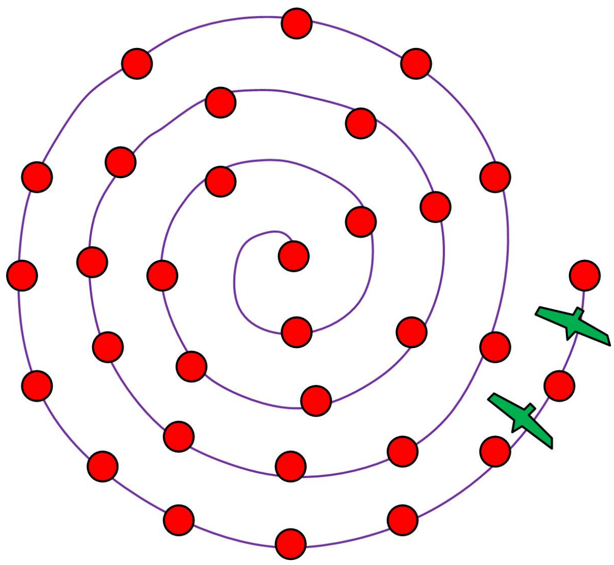

Figure 2: Vultures search for prey in a spiral

In Figure 2, the BE searches for prey in the selected search space and accelerates in a spiral shape in various directions to find the best place to dive down and capture prey. The search method is shown in equation (2).

$$P_{i,new} = P_i + x(i)(P_i - P_{mean}) + y(i)(P_i - P_{i+1}) \tag{2}$$

In equation (2), P_{i+1} represents the next update position of the $i - th$ BE. During the dive to capture prey stage, the BE quickly dives and flies towards the prey from the optimal angle of searching for space. At the same time, other BE individuals also move towards their prey. The position change is equation (3).

$$P_{i,new} = \delta P_{best} + x_1(i)(P_i - a_1 P_{mean}) + y_1(i)(P_i - a_2 P_{best}) \tag{3}$$

In equation (3),a_1 and a_2 represent the intensity of the BE's movement towards the optimal point and center point, respectively, with a value range of [1,2] . Due to the fact that the BES algorithm only relies on information exchange between individuals to search for the optimal solution, it is susceptible to the influence of local extremum when selecting the search space, greatly reducing convergence efficiency. To address this issue, this study first utilizes Sinusoidal mapping to evenly distribute the BE population in the search space, and then enhances the updated position of the BE population through crossover and non-uniform mutation operators. Finally, the flipping and foraging strategy is chosen to improve the local optimization ability of the BES algorithm during the search phase, resulting in the IBES algorithm. When multiple faults occur in a distribution network containing DG devices and the fault current information of multiple nodes is distorted, there is still significant room for improvement in the accuracy of the IBES. Therefore, this study introduces the Dijkstra to improve the IBES and obtain the D-IBES. The D-IBES algorithm uses the Dijkstra algorithm in the fault location stage to quickly narrow down the areas where faults may occur, and then uses the IBES algorithm in these areas for in-depth fault feature analysis and diagnosis. This hybrid approach accelerates fault location and enhances fault diagnosis accuracy, particularly when dealing with large-scale and complex power distribution networks. When a fault occurs in a certain section, the main power supply and DG device provide corresponding fault current to reach the fault point and collect it at that section. According to the coding of distribution network nodes and sections, the Dijkstra algorithm defines the section from the faulty node to the main power supply as the upstream part of the faulty node. The section from the faulty node to the DG or load end is defined as the downstream part of the faulty node. The path through which the fault current flows is equation (4).

$$\begin{cases} R_{i,u} = F(A_{i,u}) \\ R_{j,v} = F(A_{j,v}) \end{cases} \tag{4}$$

In equation (4), the node numbers at the outlet of the main power supply and at the outlet of the DG device are i and j . $R_{i,u}$ and $R_{j,v}$ respectively represent the set of fault currents flowing from the main power supply to the fault node and the set of fault currents provided by the DG device to the fault point. F and A represent the objective function and adjacency matrix, respectively. The paper stipulates that the direction of the main power supply flowing to the load side is positive, denoted as 1. The current direction of the DG device towards the fault point is negative, denoted as -1. Therefore, the fault current encoding method is equation (5).

$$I_i' = \begin{cases} 1, I_i' \in R_{i,u} \\ 0, Fault - free\ current\ flow \\ -1, I_i' \in R_{j,d}\ and\ I_i' \notin R_{i,u} \end{cases} \tag{5}$$

In equation (5), I_i' is the set of paths through which the fault current flows. The solution process of the D-BES is Figure 3.

In Figure 3, this study first initializes the population based on the fault current information uploaded by the feeder terminal unit, then solves the fault section using the IBES algorithm, and locates it using the Dijkstra algorithm. When the fault is located in a certain area, the IBES algorithm is used to locate the section where the fault is located.

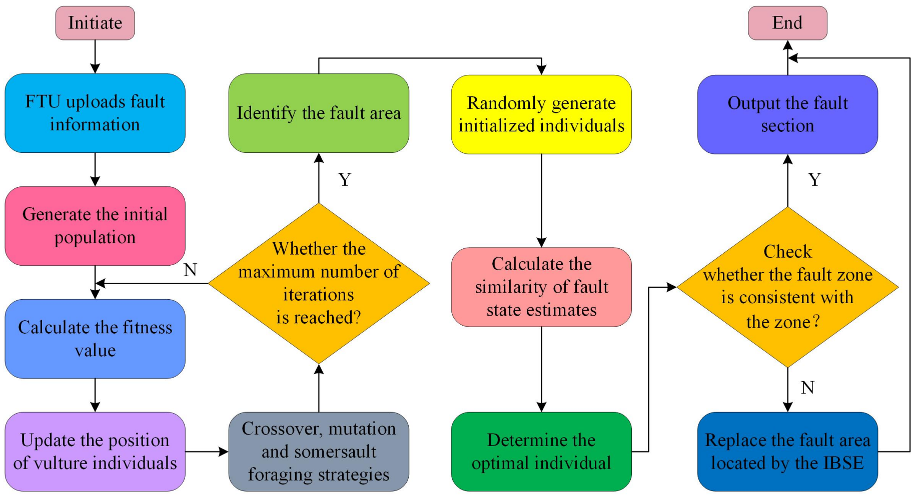

Figure 3: Solving flow of the D-IBES algorithm

3.2 Construction of FDRSN-IBS-SVM Fault Identification Model

On the basis of accurately locating the fault section, taking into account nonlinear factors such as DG device type and output power, this study introduces FDRSN and IBES to optimize the SVM and obtain the FDRSN-IBS-SVM model. This enables rapid and effective identification of fault types in distribution networks. The experiment applies IBES to the feature selection process and gradually narrows the scope of the feature set through a binary search strategy. At each step, the algorithm needs to evaluate the performance of the current feature subset and divide it into two subsets, each containing half the number of features. The above steps are performed during the running of the SVM algorithm, and each iteration will reduce the number of features until a predetermined number of features is reached or the performance is no longer significantly improved. FDRSN refers to a deep learning model used for image processing and computer vision tasks. It integrates deep residual network (DRN) and residual shrinkage module (RSM) to improve the performance and efficiency of the model through residual connections and shrinkage operations [19, 20]. DRN introduces identity paths into typical neural network structures to effectively transfer and update weight parameters, alleviating problems such as gradient vanishing and training degradation caused by increasing depth in DNN. The composition structure of DRN is shown in Figure 4.

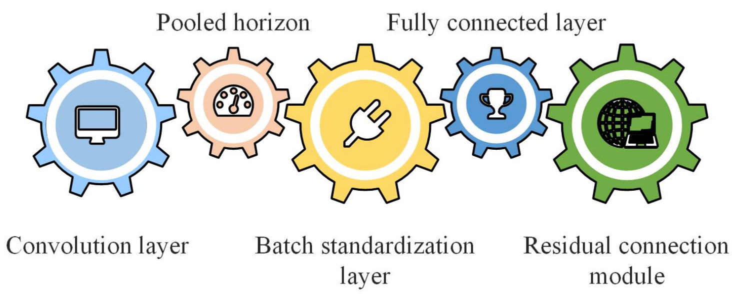

Figure 4: DRN composition structure

In Figure 4, DRN is mainly composed of five parts: convolutional layer, pooling layer, batch standardization layer, fully connected layer, and residual connection module. The process of convolution in DRN involves convolving the kernel with the input signal, adding a bias term, and obtaining features through the activation function, as shown in equation (6).

$$x_k^{(m)} = f(\sum_{c=1}^{C} \omega_k^{(c,m)} * x_{k-1}^{(c)} + b_k^{(m)}) \tag{6}$$

In equation (6), * is a convolutional operation. k and c represent the quantity of channels in the

$k-layer$ network and feature map, respectively. $x_{k-1}^{(c)}$ is the feature map where the channel in the $k-1$ layer is c . $\omega_k^{(c,m)}$ represents the convolutional kernel weight matrix with a quantity of m . $b_k^{(m)}$ is the bias weight matrix. $f()$ is the Swish function, and its mathematical expression is equation (7).

$$\begin{cases} f(x) = xsigmoid(\zeta x) \\ sigmoid(x) = \frac{1}{1+e^{-x}} \end{cases} \tag{7}$$

In equation (7), ζ is a constant, and the Swish function has the characteristics of unbounded, smooth, and non monotonic. The main function of the pooling layer is to reduce the parameters required for DRN operation and prevent over-fitting problems, as shown in equation (8).

$$X_k^{(m)} = f(\alpha_k^{(m)} down(X_k^{(m-1)}) + b_k^{(m)}) \tag{8}$$

In equation (8), $down()$ and $\alpha_k^{(m)}$ represent the down-sampling function and down-sampling multiple, respectively. To further avoid the occurrence of gradient vanishing and explosion phenomena, it is necessary to add batch standardization layers before or after the activation function of each layer. Each batch of standardized layers uses two parameter vectors to scale and move the results. The fully connected layer is also a special layer that achieves feature extraction through convolutional operations. Any basic unit is connected to any basic unit in the previous layer. The weighted sum calculation of the fully connected layer is equation (9).

$$y_{w,b}(x) = f(\sum_{i=1}^{n} w_i x_i + b_i) \tag{9}$$

In equation (9), w_i and b_i represent the weight coefficient and bias, respectively. x_i is the value of the $i-th$ neuron in the previous layer. The residual connection module is the most fundamental component of DRN. It handles the matters of gradient vanishing and insufficient expression ability in DNN by introducing skip connections and allowing information to directly propagate across layers in the network. In the residual connection module, the residual block is the basic unit. It consists of two convolutional layers, each of which is followed by a batch normalization layer and an activation function, and then the output is added to the input. Its basic structure is Figure 5.

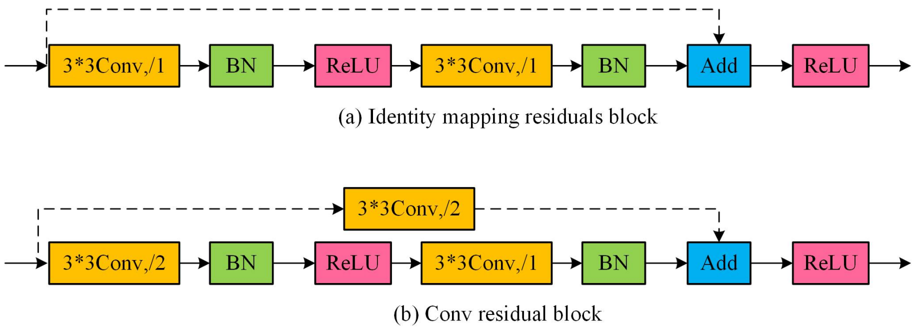

Figure 5: Basic structure of the residual connection module

Figures 5 (a) and (b) show the identity mapping and down-sampling residual modules, respectively. The identity mapping residual module consists of two or more convolutional layers. Each is followed by a batch normalization layer and activation function. RSM, as a variant of the residual module, utilizes a soft threshold function to improve the residual module. The threshold of the soft threshold function is not manually set, but is automatically set during network training, as shown in equation (10).

$$y = \begin{cases} x-\tau, x > \tau \\ 0, -\tau \le x \le \tau \\ x+\tau, x < \tau \end{cases} \tag{10}$$

In equation (10), x and y represent the input and output characteristic values, respectively. τ is the network training threshold, which may be affected by noise interference during actual data collection. Soft thresholding can set noise information to zero and discard it, while retaining current important feature information. The SVM algorithm is a supervised learning algorithm commonly used for binary classification and regression problems. It achieves classification by constructing a hyperplane or a set of hyper-planes in the feature space to separate samples of different categories. This study sets the fault sample data of the distribution network with DG devices as $\{(x_1, z_1), (x_1, z_1), .., (x_N, z_N), \}$, where $x_i \in R^m$, $z_i \in [-1, 1]$, and $i \in [1, 2, ..., N]$. There are N sample data, each of which is an M-dimensional vector with a category label of 1 or -1. The hyperplane function expression of the SVM model is equation (11).

$$h(x) = r^T x + a \tag{11}$$

In equation (11), x is the input vector. r is the weight vector. a is the aforementioned negative threshold. This study first normalizes the sample data, namely $\forall x_i$ and $|h(x_i)| \geq 1$ .The data point closest to the hyperplane is denoted by an equal sign, resulting in a classification interval of $\frac{2}{\|r\|}$. The process of minimizing $\|r\|^2$ to obtain hyperplane functions is equation (12).

$$\begin{cases} \min\limits_{w,a} \frac{1}{2} r^T r \\ s.t. z_i(r^T x_i + a) \geq 1 \end{cases} \tag{12}$$

Equation (12) can be solved using the idea of optimization and the Lagrange multiplier method to obtain the linear kernel function as shown in equation (13).

$$h(x) = \sum_{i=1}^{N} b_i z_i < x.x_i > +a \tag{13}$$

In equation (13), $a = z_i - \sum_{i=1}^{N} z_i b_i^* < x.x_i >$ and $b^* = \{b_1^*, b_2^*, ..., b_N^*\}$ are the optimal solutions obtained. Therefore, the structure of the FDRSN-IBS-SVM fault identification model is Figure 6.

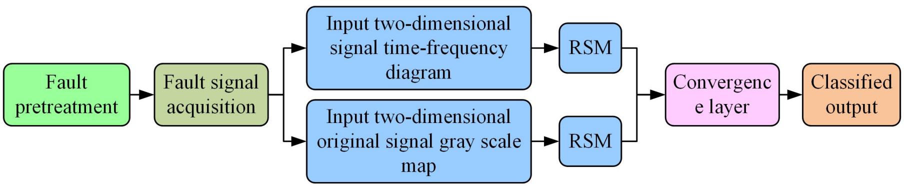

Figure 6: Solution process of FDRSN-IBS-SVM fault identification model

In Figure 6, the training process starts with the collection and preprocessing of historical fault data, which is used to train the FDRSN-IBS-SVM model. First, the raw data are preprocessed using the FDRSN method to deal with the uncertainty and incompleteness of the data. Next, the intelligent bee swarm (IBS) algorithm is used for feature selection. The objective of this step is to identify and retain the features that are most relevant to fault identification. This will improve the efficiency and accuracy of the model. Finally, a SVM classifier is trained using these selected features. The process of testing involves introducing new, unseen data into the trained model and assessing the model's capability to identify types of faults. The performance of the model can be evaluated by comparing its predictions with actual failure types. The data extracted during the real-time monitoring process of the distribution network are used as input features of the model. The input features for the distribution network include electrical parameters such as current, voltage, power, and frequency, as well as transient signals that may indicate fault conditions. Different types of faults that occur during the operation of the distribution network, such as short circuit, ground fault, overload, etc., are regarded as output categories. The goal of building the FDRSN-IBS-SVM fault identification model is to accurately classify and identify these fault types based on input features.

The evaluation indicators selected for the experiment are the CPU loss rate, accuracy rate and recall rate of the model. In the context of distribution network faults, the accuracy is calculated as the ratio of the number of correctly predicted fault samples to the total number of samples. The CPU loss rate refers to the proportion of the average power outage time of customers or residential buildings in the distribution network due to faults. The recall rate measures the proportion of the number of fault samples correctly identified by the model to the number of actual fault samples, with a maximum value of 1. The above indicators are selected because they can evaluate the fault detection capabilities of the model from different perspectives, among which the CPU loss rate is directly related to the operating efficiency and user satisfaction of the distribution network. Based on the above, the node distribution of the multi-source node distribution network of the DG device is shown in Figure 7.

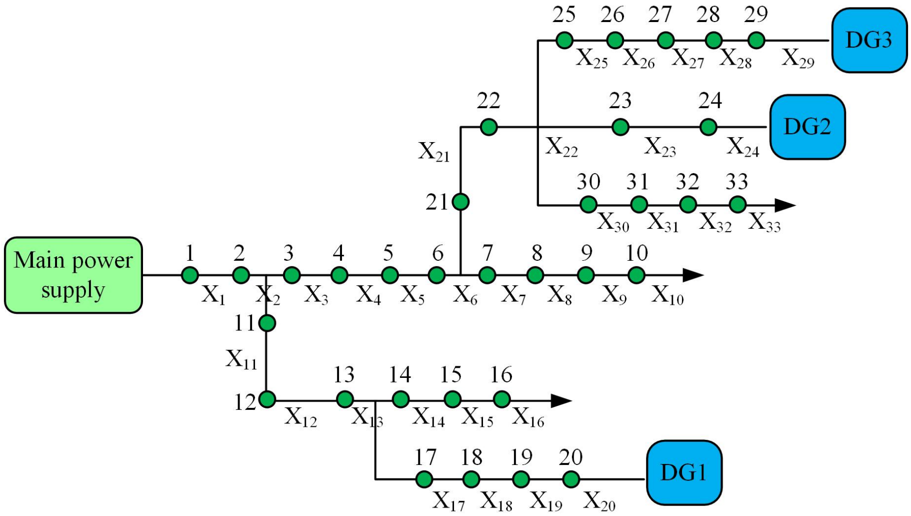

Figure 7: Multi-source node distribution network with DG device

Figure 7 shows a multi-source 33-node distribution network with a total of 33 sections and nodes. The feeder nodes are numbered 1 33, while the section numbers are X1 X33. DG devices are connected at the back end of nodes 20, 24, and 29. S is the main power supply of the system, and DG1, DG2 and DG3 are three distributed power supplies. According to the definition rules of regional division, the distribution network is divided into ten independent areas. First, the BES parameters are initialized, the number of populations are set to 50, the spiral angle is 10, the number of spiral search cycles is 1.5, and the maximum number of iterations is 200. FDRSN has a total of 18 convolutional layers, and the learning rate of FDRSN is set to 0.0075. To more accurately select the optimal training size, the accuracy of each iteration is recorded during training, and Adam is used to optimize the parameters. Finally, the test data is input into the trained FDRSN model, and the final average test accuracy is calculated. The experimental hardware platform is a personal computer with an IntelG4400 processor, a main frequency of 3.30GHz, and a memory of 4GB to implement simulation tests in the MATLAB2018B environment.

4 4 Result and discussion

To verify the effectiveness and feasibility of the IBES-based fault location and identification model in distribution networks with DG, multiple control groups were set up for experiments.

4.1 Fault Location Analysis of D-IBES Algorithm

The experiment selected the IBES algorithm, the distribution system fault location method based on deep graph convolution network (DL-GCN) [21], and compared the performance with the D-IBES algorithm. Since fitness was an indicator used to measure the performance of the solution algorithm in intelligent optimization algorithms, it could directly reflect changes in the degree of convergence during the operation of the algorithm. The faster the fitness value reached stability, the better the convergence performance of the algorithm. Therefore, the fitness was compared between the two cases of no-information distortion and node information distortion, as shown in Figure 8.

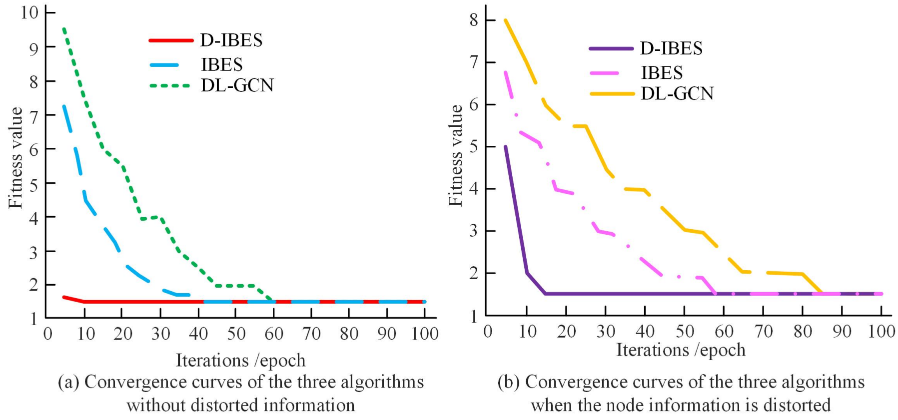

Figure 8: Convergence results of fault location in two cases

Figure 8(a) is the convergence result of distribution network fault location when there is no distortion information. As the system operation iterations increased, the fitness values of the three algorithms began to decrease. At the 10th iteration, the D-IBES algorithm reached a stable state of operation, while the IBES and DL-GCN algorithms achieved stable fitness at the 40th and 60th iterations, respectively. Figure 8(b) is the fault location convergence result when there is information distortion in the node. When the system iterated to the fifth time, the fitness values of D-IBES, IBES and DL-GCN algorithms were 5.0, 6.9 and 8.0 respectively. When the system iterated to the 15th time, the fitness value of the D-IBES algorithm stabilized at 1.5. At the 58th and 85th iterations, the fitness values of the IBES and DL-GCN algorithms respectively began to stabilize. When using the D-IBES algorithm to locate faults without distortion information and with distortion information, the fitness value quickly reached a stable state as the number of iterations increased, and reached a stable state in a short time. A lower level, which showed that the algorithm could effectively locate faults and reach a convergence state relatively quickly. The Sinusoidal mapping was utilized in the D-IBES model to address the limitations of the traditional BES algorithm, which could become trapped in local optima and struggle to update population positions quickly. Then the CPU loss rate and average time consumption of the D-IBES algorithm and the IBES algorithm were compared. The specific results are shown in Figure 9.

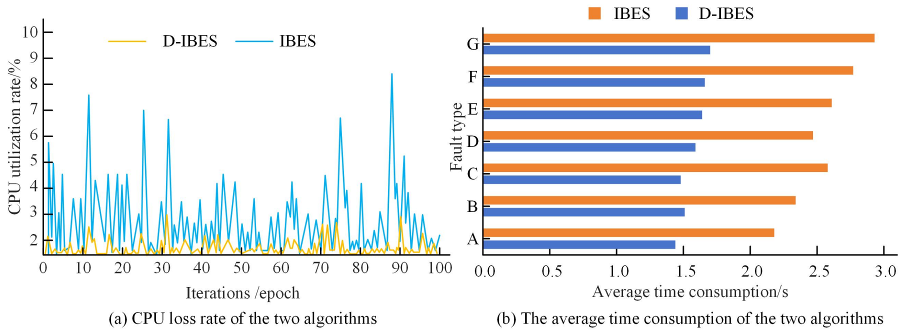

Figure 9: CPU loss rate and average time-consuming results of two algorithms

Figure 9(a) is the CPU loss rate result, which is equal to total power outage time and total power supply time. The average CPU loss rate of the IBES algorithm was 2.83%, and the average CPU loss rate of the D-IBES algorithm was 0.54%. The comparison showed that the D-IBES algorithm was more efficient than the IBES algorithm in utilizing CPU resources and had a lower CPU loss rate. This directly showed that when the D-IBES algorithm was applied, the reliability of the distribution network and the stability of users' power consumption were better. In real-time fault diagnosis, a lower CPU loss rate helped the system quickly identify and respond to obstacles, thereby reducing power outage energy consumption and time-consuming, improving user satisfaction and power grid service quality. Figure 9(b) shows the average time-consuming results of the two algorithms under different fault locations and distortion points. By measuring the actual time taken for each diagnosis and calculating the average, the average time taken by the algorithm could be obtained. Among them, A represented the experimental scenario where there were no other distorted nodes at fault node 5. B represented the fault scenario where the fault location was at node 5 and the distortion points were at nodes 18 and 22. C was the fault scenario where the fault location was at nodes 5 and 18, and there were no other distorted nodes. D was a fault scenario in which the fault locations were at nodes 5 and 18, and the distortion points were 7, 15, and 32 nodes. E was a fault scenario in which the fault locations were at nodes 5 and 18, and the distortion points were 2, 16, 21, and 28 nodes. F was the fault scenario where the fault locations were at nodes 10, 19 and 21, and the distortion points were 2, 17, 27 and 33 nodes. G was a fault scenario in which the fault locations were nodes 8, 15, 19, and 33, and the number of distortion points was nodes 3, 12, 22, and 29. Taking scenarios A, D and G as an example, the average time consuming of the D-IBES algorithm was 1.44s, 1.59s and 1.70s respectively. The average time consuming of the IBES algorithm was 2.18s, 2.47s and 2.93s respectively. This showws that the D-IBES algorithm consumes less system running time under different fault scenarios and could improve the speed of positioning. The shorter average time consumption showed that the algorithm could respond quickly and provide decision support for rapid recovery and fault handling of the distribution network, thereby reducing economic losses and improving the operating efficiency of the power grid. This also proved that after the Dijkstra algorithm was introduced in the experiment, the D-IBES algorithm was more efficient in fault location, but consumed less resources. It could quickly locate faults in the distribution network. The introduction of the Dijkstra operation was correct and effective.

4.2 Fault Identification Analysis of FDRSN-IBS-SVM Model

Based on the research results obtained in the previous section, the experiment then verified the effectiveness and feasibility of the FDRSN-IBS-SVM fault identification model. The comparison methods selected in the experiment were FDRSN algorithm, SVM algorithm, fusion of complex network theory, and renewable energy. The performance of the disaster-resistant line identification method of the power system core skeleton network Complex Network-CSN (CN-CSN) [22, 23] was compared with the D-IBES algorithm. First, a data set of distribution network fault types under different load levels and different DG device types was selected for experiments. The fault identification accuracy results of the four algorithms are shown in Figure 10.

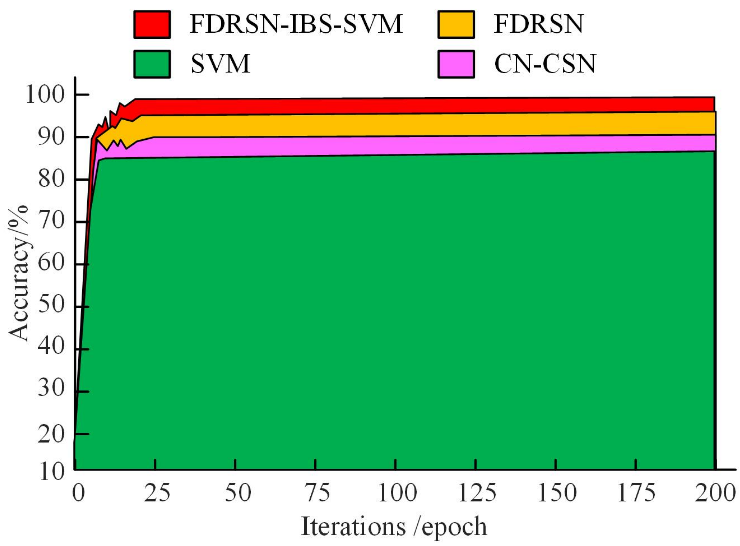

Figure 10: Results of fault identification accuracy of four models

Figure 10 shows the fault identification accuracy results of the four models. As the number of iterations increased, the accuracy of the four models increased. Finally, the accuracy of the FDRSN-IBS-SVM model was 99.05%. The accuracy of the FDRSN model was 94.83%, the accuracy of CN-CSN was 90.29%, and the accuracy of SVM was 86.41%. The comparison showed that the FDRSN-IBS-SVM model was significantly more accurate than other algorithms. This was due to the fact that the FDRSN-IBS-SVM model combined more complex algorithms and used more data features. The structural design of the remaining three comparison algorithms was simpler than the FDRSN-IBS-SVM model, so the recognition accuracy obtained was obviously smaller. In distribution network fault diagnosis, the FDRSN-IBS-SVM model had a high accuracy and could accurately identify and classify various faults, thereby providing a more reliable decision-making basis for power grid operation and maintenance personnel. This was because the FDRSN model could handle uncertainty and noise in distribution network data, improve data quality, and provide more accurate input for subsequent feature selection and classification. In addition, to prove that the FDRSN-IBS-SVM model was not affected by the power output of the DG device, the study also calculated the accuracy results of each model under different output powers of the DG device under the original load level, as shown in Table 1.

Table 1: Accuracy results of four models under different output power of DG device

DG device type	Output rating	FDRSN-IBS-SVM	FDRSN	CN-CSN	SVM
Wind power	40%	99.05%	94.83%	90.79%	86.52%
Wind power	70%	99.21%	94.42%	89.54%	85.58%
Photovoltaics	50%	98.54%	94.26%	89.92%	85.84%
Photovoltaics	70%	98.81%	93.58%	90.77%	85.72%
Wind power+Photovoltaics	50%+70%	98.97%	93.89%	89.91%	85.88%
Wind power+Photovoltaics	100%+40%	99.24%	94.61%	90.35%	86.53%

In Table 1, when the wind power DG transposed output power was 40%, the accuracy rates of the four models of FDRSN-IBS-SVM, FDRSN, CN-CSN and SVM were 99.05%, 94.83%, 90.79% and 86.52% respectively. When the photovoltaic DG transposed output power was 70%, the accuracy of the FDRSN-IBS-SVM model was 98.81%, which was higher than the 93.58%, 90.77%, and 85.72% of the FDRSN, CN-CSN, and SVM models. When the output power of the wind power+photovoltaic integrated DG device was 100% and 40%, the accuracy of the FDRSN-IBS-SVM model was 99.24%, the accuracy of the FDRSN model was 94.61%, the accuracy of CN-CSN was 90.35%, and the accuracy of SVM was 86.53%. The FDRSN-IBS-SVM model demonstrated superior accuracy in fault location identification, even when the DG device type and output power differed from those of the other three models. It could reduce resource waste and unnecessary maintenance work caused by model misreporting data, improve the efficiency and economy of fault handling, and help to take preventive measures in advance to avoid potential power grid damage. This was mainly because the FDRSN module was introduced in the FDRSN-IBS-SVM model. This integration effectively transferred weight parameters and updated the system structure, ultimately mitigating the training degradation problem and improving the accuracy of fault identification. The distribution network was a complex system that existed in the real world. Its operating environment would be affected by various noises, including electrical noise, environmental interference, and Gaussian noise. These faults would lead to short circuits, overloads and equipment failures in the distribution network. Due to the Gaussian white noise was often used as a model to simulate random noise in the real world, it had the convenience and applicability of mathematical calculations. At the same time, when the deep learning algorithm was running, the level of Gaussian white noise had a greater impact on the effects of real-world applications and data calculations. Therefore, Gaussian white noise was selected in the experiment to further verify the stability of the algorithm. The study added 1%, 2%, 3%, 4% and 5% Gaussian white noise corresponding to the signal-to-noise ratio in the test set for testing. The test results are shown in Figure 11.

Figure 11(a) is the accuracy result after adding Gaussian white noise interference. When the Gaussian white noise was 5%, the accuracy of the FDRSN-IBS-SVM model was 97.89%, which was much greater than the 93.58%, 88.12% and 81.87% of FDRSN, CN-CSN and SVM. Figure 11(b) is the recall result after adding Gaussian white noise interference. When the Gaussian white noise was 5%, the recall rates of the four models of FDRSN-IBS-SVM, FDRSN, CN-CSN and SVM were 97.54%, 93.89%, 88.13% and 79.84% respectively. When Gaussian white noise was added to the original data, the accuracy of each model decreased to a certain extent. However, compared to the other three

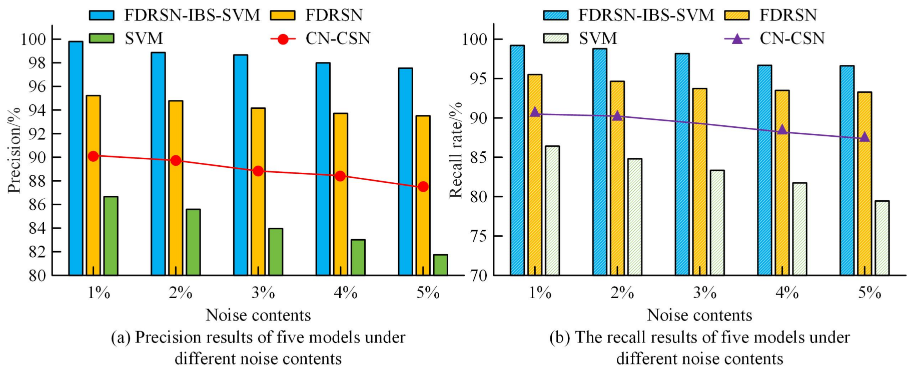

Figure 11: Performance evaluation of four models with noise interference

models, the performance of the FDRSN-IBS-SVM model was less affected by noise, which also showed that the FDRSN-IBS-SVM model had good noise immunity. The main reason for this phenomenon was that the addition of Gaussian noise affected the internal structure of the built model, but the FDRSN-IBS-SVM model had less impact because it incorporated a variety of algorithms.

4.3 Discussion

Distribution network is an important part of the power system, and its fault diagnosis is crucial to ensure the safe and stable operation of the power system. Traditional distribution network fault diagnosis methods mainly rely on manual inspection and expert experience. These methods consume significant time and human resources and are limited by expert experience and inspection scope. They often fail to detect and diagnose faults accurately and in a timely manner. To intelligently diagnose distribution network faults, an intelligent diagnosis algorithm for distribution network faults based on deep learning is proposed in the experiment. This method uses DNN to learn fault data and automatically extract key features, achieving rapid and accurate identification of fault types. In addition, the algorithm also takes into account the dynamic changes and uncertain factors of the distribution network, and introduces FDRSN and IBES to optimize the SVM model to improve the robustness of fault diagnosis.

The proposed diagnostic algorithm is compared with the IBES algorithm, FDRSN algorithm and SVM algorithm, etc., and it is proved that the algorithm proposed in the experiment has higher diagnostic accuracy and faster diagnostic speed. This is because the constructed method includes the D-IBES model and the FDRSN-IBS-SVM model. Sinusoidal mapping is also introduced into the D-IBES model, which can reduce the possibility of the traditional BES algorithm falling into local optima and achieve rapid convergence [24]. The combination of the FDRSN-IBS-SVM model and the FDRSN module allows the weight parameters to be effectively transferred. The system structure is updated, which ultimately effectively alleviates the training degradation problem and correctly improves the accuracy of fault identification [25]. This can not only cope with the uncertainty, randomness, complexity and other challenges existing in the current distribution network system, but also provide new ideas and opportunities for future technological development.

For distribution network operators, the intelligent diagnosis algorithm proposed in the study can significantly improve the efficiency and accuracy of fault handling, reduce operation and maintenance costs, and ensure the stable operation of the power grid. For researchers, the experiment provides a new deep learning application scenario and distribution network fault diagnosis method, and promotes interdisciplinary research cooperation and technical exchanges. To implement the proposed method practically, it is recommended that distribution network operators establish a complete fault data collection and management system. This system will provide data support for the training and optimization of deep learning models. Scientific researchers should continue to steadily explore the advantages of deep learning models, improve its potential in fault diagnosis, and continuously optimize the algorithm structure and parameter optimization to improve the generalization ability and adaptability of the model. Scientific research departments should encourage industry-university-research cooperation from all walks of life to jointly promote the industrial application of intelligent diagnostic algorithms and realize the transformation of technological achievements.

Although the experiment has achieved certain results, there are still certain limitations. For example, the scalability of the D-IBES algorithm when dealing with larger-scale networks has not been fully verified. The adaptability of the FDRSN-IBS-SVM model to emerging fault types also requires further research. Furthermore, the effective integration of the obtained results with existing fault management systems has always been a topic of interest for research. This also means that future research can be further expanded towards the processing power, adaptability, flexibility and integration of algorithms in the model.

5 Conclusion

This study proposed a novel two-stage approach for fault location and identification in distribution networks with DG. The D-IBES algorithm, combining the IBES algorithm with the Dijkstra algorithm, achieved efficient and accurate fault location. The FDRSN-IBS-SVM model, integrating the FDRSN with IBES and SVM, demonstrated high fault identification accuracy and robustness to noise. Experimental results validated the superior performance of the proposed approach compared to existing methods. The study presents two main contributions. Firstly, the D-IBES algorithm is developed for fault location in distribution networks with DG. Secondly, the FDRSN-IBS-SVM model is proposed for fault identification, taking into account nonlinear factors such as DG type and output power. The proposed approach offers a promising solution for intelligent fault diagnosis in modern distribution networks. Future research could focus on extending the approach to larger networks, adapting to new fault types, and integrating it with existing fault management systems.

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