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Computer Vision Search System for the Identification of Power Flow Faults in Micro Electric Networks

Yonghui Yang[1*]

[1] Pingdingshan Polytenchnic College
Pingdingshan (China)
E-mail: **zpskyyh@sina.com**

Abstract. To improve the safety of microgrid operation, this paper uses a computer vision search system to study the identification of power flow faults in microgrids. Firstly, a power flow fault detection method based on a message transmission network was proposed, and the fault mapping from the microgrid fault to each node was constructed, and the power flow fault of each node in the microgrid was extracted. Then, by migrating the long short-term memory network to identify power flow faults in microgrids, the influence of computer vision search system on power flow fault identification in microgrids was comprehensively analyzed. The simulation results show that the proposed method can effectively improve the accuracy of power flow fault identification in the microgrid to improve the safety of the microgrid operation.

Key words. Computer, Visual Search System, Micro Electric Network, Power Flow Fault Identification.

1. Introduction

Microgrids are sustainable power generation and distribution systems composed of three parts: distributed generation, energy storage systems, and power loads. These are important parts of the future development of China's power grid. Microgrids inherit many characteristics of smart grids, such as the self-healing ability of the grid [1], real-time monitoring of distributed generator sets, and high permeability, which can effectively improve the quality and stability of power grids. However, in order to realize the safe and reliable operation of microgrids [2], it is necessary to carry out fast and accurate fault detection, identification and protection mechanisms for relevant microgrids, so as to shorten the line inspection time in microgrids, reduce the power outage time of the power grid, reduce the economic loss of the power grid, and improve the overall reliability of the microgrid [3]. Therefore, identifying power flow faults in microgrids is of great significance for maintaining and operating microgrids. Therefore, this paper applies a computer vision search system to microgrids to identify power flow faults in the network and verify the effectiveness of the proposed method [4].

2. Related Works

At present, most fault diagnoses in microgrids rely on the operation data of various components in the power grid [5], and the rapid development of information technology has led to the wide application of computer vision search systems. This paper proposes a power flow fault identification algorithm for microgrids based on the wavelet transform coefficient. Based on the characteristics of the wavelet transform, the window expansion method is used to adapt to the threshold of the wavelet coefficient difference during the window expansion process [6]. Compared with the existing threshold methods, the wavelet transform algorithm can better adapt to different data samples, and at the same time, the threshold can be reasonably adjusted for the fault states of different power grids, so it has a strong sensitivity to power flow faults in microgrids. Through a series of experiments, it is verified that the fault identification method using wavelet transform can identify power flow faults under different fault conditions, but the overall recognition time of the method is slow. In this paper, a power flow fault identification method based on random matrix theory is proposed and applied to microgrids' power flow fault identification. Specifically, by collecting the voltage and current data of each node in the microgrid, the microgrid sample data matrix is established, and then the time and type of power flow faults in the microgrid are judged from the time dimension and the spatial dimension so as to carry out multiple analysis. Some studies show that compared with other fault identification methods, the intelligent algorithm can effectively expand the specific range of power flow fault detection, thereby shortening the power flow fault identification time, but this method does not improve the accuracy of power flow fault identification in microgrid, so the combined braking method can improve the calculation accuracy [7]. In this paper, a power flow analysis technology based on a computational visual search algorithm is proposed to identify power flow faults in microgrids. According to the power flow fault identification code formed by the microgrid structure, the expected value and operation state of the power grid fitness function are constructed from the expected relationship between the power flow change of the protection microgrid and the state of the power grid equipment, so as to improve the fault tolerance of the collected information in the power grid and improve the overall optimization ability of the computational visual search algorithm through the variation and cross calculation in the computational visual search algorithm. The simulation model verifies the effectiveness of the proposed algorithm. Experimental results show that the proposed computational visual search algorithm can overcome the influence of information loss and error on power grid fault identification. The computational visual search algorithm analyzes the correlation between the microgrid's device state and the microgrid's power flow change, which improves the accuracy of power flow fault identification in the microgrid but has the problem of prolonging the fault identification time [8].

3. Power Flow Fault Detection of Micro Electric Network Based on Message Transmission Network

A. Power Flow Fault Detection

Firstly, each electrical node in the micro electric network is extracted from the node state of the power grid based on the observation data. The measurement of each node in the micro electric network is input into the computer vision search system, and the local node state characteristics in the micro electric network are extracted, which are expressed as follows:

$$\chi = c(x;\theta_1) \tag{1}$$

In the above equation (1), the feature matrix of the electrical node state in the micro electric network is described, the dimensionality of the node features extracted, the node feature extraction model in $\chi \in R$ the computer vision search system is described, and the parameters θ_1 of the detection model are described.

B. Judgment of Trend Type

According to the real-time operation status of the micro electric network, the topological features are input to realize the update of the node features, and the updated node features are retained, and the result of the output node running state prediction is as follows, which can be described as: y

$$y = S(\chi, A;\theta_2) \tag{2}$$

In equation (2), S represents the constructed model of power flow fault detection R_{N_m}, the parameters of information transmission θ_2, the probability matrix of the state of electrical nodes in the power grid, and the total number of node prediction state $y\, s \in N_m$.

C. Fusion of Voltage and Current between Microgrids

The state characteristics of all nodes in the micro electric network are input into the fully connected network, and the probability matrix of node anomalies and the power flow fault label matrix can be output.

$$(P, Y) = e(y) \tag{3}$$

$$g(y, A) = g(P, U(Y, A)) \tag{4}$$

In equations (3) and (4), the node label matrix in the micro electric network is specifically the label with the highest output probability for each node after passing the model mapping e, which represents the label mapping, U represents the line mapping, and locates and infers the fault line.

Through supervised learning, the information samples with labels are calculated, and the learning model is established, and the process of predicting the probability optimization of node labels in the original micro electric network is transformed into a parameter optimization problem θ_1^*, and the optimal parameter sum θ_2^* is obtained, that is,

$$\theta_1^*, \theta_2^* = \underset{\theta_1,\theta_2}{\operatorname{argmax}} \prod_k \varsigma\left(Y_k = \hat{Y}_k \middle| X_k;\theta_1,\theta_2\right) \tag{5}$$

In equation (5), the optimal parameters obtained from the solution are denoted to represent the model of probabilistic prediction θ_1^*, and the measurement matrix of the input of the data sample is deputized θ_2^*. According to the power flow fault location requirements ς in the micro electric network X_k, the above formula is transformed into a loss function k, and the parameters in the formula are updated by gradient descent training algorithm.

D. *Diagnosis of Photovoltaic and Wind Power Grids*

In a micro electric network, when a single line fails, only two of the nodes can be used as fault labels, resulting in an imbalance between the number of fault labels and the number of normal labels. The imbalance of data will make it difficult for the detection model to learn fault features L, so the weights negatively correlated with the number of labels are introduced to improve the effect of the power flow fault detection model on the learning of power flow fault labels, which can be calculated as follows:

$$L = -\sum_{i=1}^{n} w_i y_i \ln p_i \tag{6}$$

Combined with the above equation (6), it can be seen that the power flow fault location network designed in this paper can be projected in the neural network model of the micro electric network, which can help to improve the performance of the computer vision search system for power flow fault location.

The message-passing network mainly forms the feature vector of the power grid node by passing the information of the neighbor nodes in a loop, and the convolution operation of the multi-layer graph is regarded as the multiple message propagation. The messaging network constructed in this paper consists of four layers, and the process of network messaging at each layer is represented as follows:

$$\begin{cases} h_{N(i)}^{(l+1)} = G\left(\left\{h_j^l, \forall j \in N(i)\right\}\right) \\ h_i^{(l+1)} = \sigma\left(Wc\left(h_i^l, h_{N(i)}^{(l+1)}\right)\right) \\ h_i^{(l+1)} = n\left(h_i^{(l+1)}\right) \end{cases} \quad (7)$$

Equation (7), represents the aggregation features generated by the first convolution G of all neighboring nodes in the micro electric network $h_{N(i)}^{(l+1)}$, and the node characteristics $h_i^{(l+1)}$ of the micro electric network nodes after convolution i are the W weights, and the way of message aggregation. In this paper, the message aggregation method is mainly used to aggregate the messages of the nodes in the micro electric network, and the aggregate function formula can be $G^{(l)}$ expressed as:

$$G^{(l)} = m\left(\left\{\sigma\left(Wh_j^l + b\right), \forall j \in N(i)\right\}\right) \quad (8)$$

In equation (8), the maximum value of the m selected feature is represented and the b biased parameter is described. In the case of this aggregation, all neighbor nodes will undergo nonlinear changes, and after feature extraction, the feature information of the micro electric network nodes will be formed.

If the weights of each edge of the node are added, the aggregation process can be expressed as:

$$h_{N(i)}^{(l+1)} = G\left(\left\{e_{ji} h_j^l, \forall j \in N(i)\right\}\right) \quad (9)$$

In equation (9), the weights between the nodes of the micro electric network j and the nodes of the micro electric network i are Represented, and the power flow fault detection e_{ji} in the micro electric network is completed by the above process.

4. Constraint and Diagnosis of Microgrid Power Flow Faults

Combined with the results of the above message connection network to detect power flow faults in the micro electric network, the computer vision system is used to identify the power flow faults in the micro electric network.

A. Diagnosis of Photovoltaic Wind Power Flow

Transfer learning is a learning method that transfers the old trained model and parameters to the new model, and then applies them to the new domain D_S.

The loss function of a transfer learning network is expressed as:

$$\ell = \ell_c\left(D_S, y_S\right) + \lambda \ell_A\left(D_S, D_T\right) \quad (10)$$

In equation (10), the final loss of the transfer learning network is described ℓ, the loss of the transfer learning network ℓ_c in the source domain data, and the adaptive loss in the transfer learning network is reflected $\left(D_S, y_S\right)$, and the difference in data and distribution between the source domain and the target domain is reflected ℓ_A, and the purpose of adaptation $\left(D_S, D_T\right)$ is to strengthen the correlation between different data sets.

B. Fault Diagnosis of Transient Power Flow

The domain adaptive network takes the maximum mean difference as the adaptive loss $MMD(X, Y)$, and the maximum mean difference measures the distribution difference between the source domain and the target domain data. Assuming that the node feature mapping function in the micro electric network is ϕ, then the empirical estimation of the maximum mean difference of the datasets in the micro electric network is defined, which is denoted as:

$$MMD(X, Y) = \frac{1}{n}\sum_{i=1}^{n}\phi(x_i) - \frac{1}{m}\sum_{j=1}^{m}\phi(y_i)_H^2 \quad (11)$$

In the official, $\|\cdot\|_H$ denotes the Hilbert space norm.

Expanding the formula for empirical estimation of the maximum mean difference, it is concluded that:

$$MMD(X, Y) = \frac{1}{n^2}\sum_{i=1}^{n}\sum_{i'}^{n}\phi(x_i) \quad (12)$$

From the above equation (12), it can be seen that to calculate the maximum mean difference in different datasets, it is necessary to know the expression of the node feature x mapping function in the micro electric network $y\phi$, but in general, it is difficult to define, so the kernel function is introduced, and the inner product of the high-dimensional vector ϕ can be obtained from the low-dimensional data through the kernel function. The above formula can be redefined and expressed as:

$$MMD(X, Y) = \frac{1}{n^2}\sum_{i}^{n}\sum_{i'}^{n}k\left(x_i, x_i'\right) \quad (13)$$

The kernel function uses the Gaussian kernel function, which is specifically expressed as:

$$k(u, v) = e\frac{-u - v^2}{\sigma} \quad (14)$$

In equation (14) above, u, v any two points of the space are separated D_S. Based on a large number of labeled network source domain data D_T and some unlabeled network destination domain data, the maximum mean difference between different datasets is expressed as follows:

$$MMD(X, Y) = \frac{1}{N^2}\sum_{i}^{N}\sum_{i'}^{N}k\left(x_{S_i}, x_{S_i}'\right) \quad (15)$$

C. Comprehensive Fault Inference of Microgrid Power Flow

Through the transfer learning of equation (15), the knowledge can be better extracted and the knowledge in the target domain can be updated and learned. Combined with the empirical estimation formula of the loss function of the long short-term memory network and the calculation of the maximum mean difference, the loss function of the migrated long short-term memory network model $\ell_{TL-LSTM}$ can be expressed as:

$$\ell_{TL-LSTM} = MSE(D_S, y_S) + \lambda MMD^2(D_S, D_T) \quad (16)$$

In equation (16), the error of the labeled network source domain datasets in the migration of the long short-term memory network model is described, and the distance between the labeled network source domain data and the unlabeled network target and the data distribution is described. Figure 1 illustrates the detailed process of the computer vision search system to identify power flow faults in a micro electric network.

$$MSE(D_S, y_S)\ell_{TL-LSTM} = MS\lambda MMD^2(D_S, D_T) \quad (17)$$

The fault diagnosis process of the power flow is as follows, as shown in Figure 1.

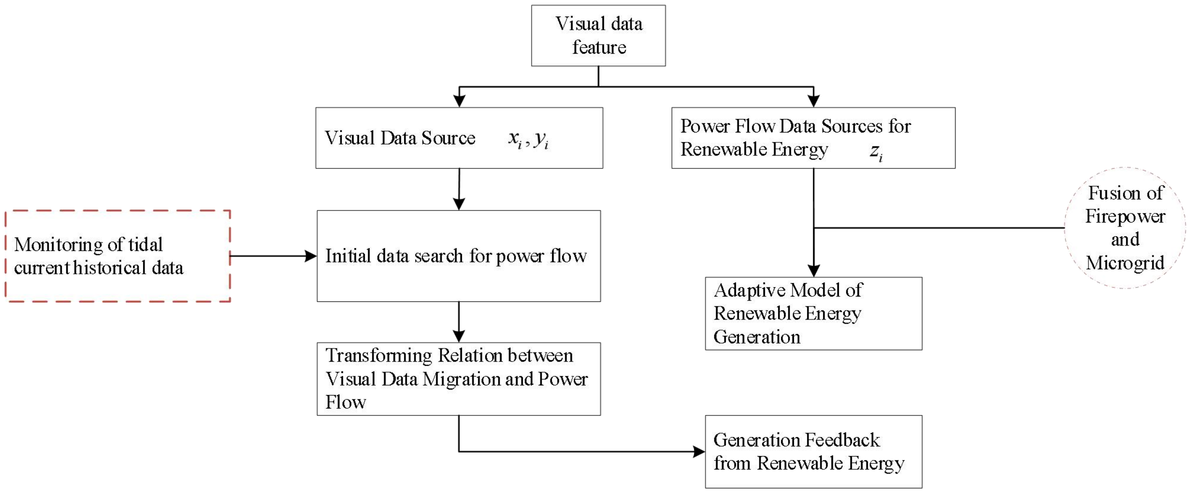

Figure 1. Power Flow Fault Identification Process in a Microelectronic Network

The main goal of the loss function of the migrated long short-term memory network model proposed in this paper is to map the source domain power flow fault data in the micro electric network and the power flow fault data in the target domain to the high-dimensional space, reduce the distance of the distribution of different data sets in the high-dimensional space, and improve the practicability of the migrated long short-term memory network model [8].

5. Experimental Results and Analysis

A. Introduction to Power Flow in Microgrids

In order to verify the effectiveness of the computer search vision system proposed in this paper for power flow fault identification in micro electric networks, simulation experiments are carried out in a Matlab simulation environment. Table 1 represents the operating parameters of micro electric networks, and Table 2 represents the structure of power flow fault identification experimental group.

Table 1. Operating Parameters of the Microelectronic Network

Parameter	**Numeric Value**
Mainnet	10 kV, 50 Hz
Output power of photovoltaic power generation/MW	0.55
The power of the battery/MW	1
The output power of wind turbine power generation/MW	0.52
load	Constant power load 1 MW×4

A schematic diagram of the operation of the microgrid is shown in Figure 2.

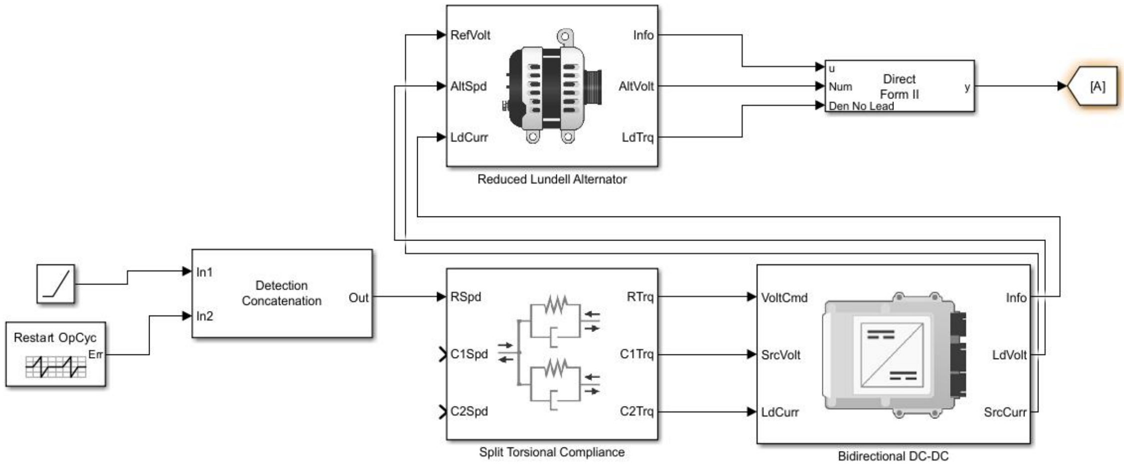

Figure 2. Schematic Diagram of the Operation of the Power Flow of the Microgrid

Then, nodes were selected for the power flow operation diagram, and the data of different nodes was analyzed for the whole network and the power flow results of each node were judged, as shown in Table 2.

Table 2. Structure of the Power Flow Fault Identification Experimental Group

The Serial Number of the Experimental Group	Total Amount of Data/Group	Normal Data/Group	Failure Data/Group
1	100	80	20
2	100	75	25
3	100	70	30
4	100	85	15
5	100	80	20

B. Accuracy of Identification of Power Flow Faults in Microgrids

The method proposed in this paper (the method in this paper is called the new method) is compared with the other two methods to compare the accuracy of power flow fault identification in micro electric networks, and the comparison chart of the experimental results is shown in Figure 3.

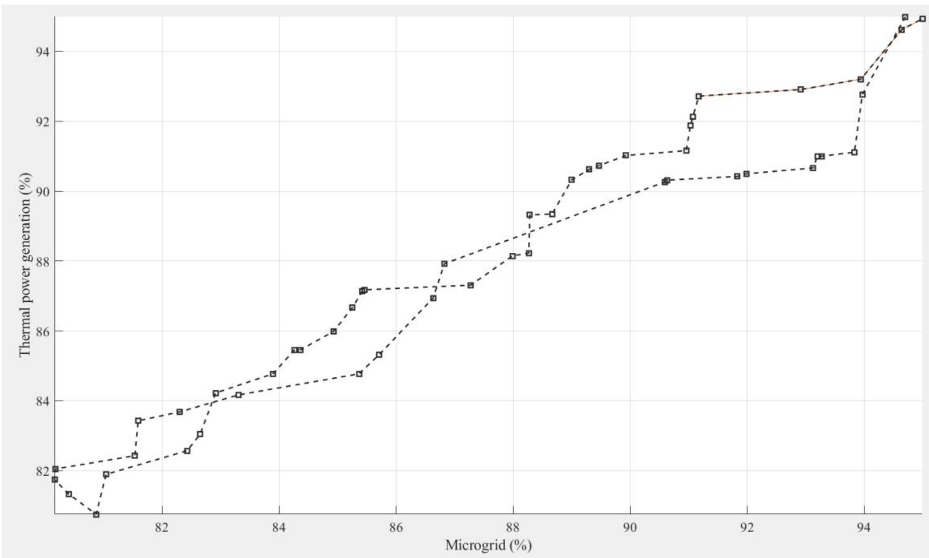

Figure 3. Comparison of the Accuracy of Power Flow Fault Identification by Different Methods

The analysis of Figure 3 shows that the identification rate of power flow faults in micro electric networks is significantly improved after the method proposed in this paper is adopted, and the reliability of the proposed method is generally higher than that of the other two methods [9]. The in-depth analysis of the experiment shows that although there are certain requirements for the number of power flow fault data in the micro electric network, the method proposed in this paper can identify the power flow fault in the micro electric network, and the overall identification accuracy is relatively high. The contribution of the proposed method to the power flow fault identification results in micro electric networks is shown in Table 3.

Table 3. Contribution of Power Flow Fault Identification Results

Power Flow Fault Information/Bytes	Contribution
1000	0.96
2000	0.95
3000	0.94
4000	0.93
5000	0.92

It can be seen from the contribution degree of the power flow fault identification results in Table 3 that the maximum overall contribution of the proposed method to the power flow fault identification results in the micro electric network is 0.96, although the contribution will decrease with the gradual increase of fault information, the overall decrease is not obvious. It shows that the method proposed in this paper can effectively improve the efficiency of micro electric network operation [10].

B. Identification Time of Power Flow Faults in Microgrids

There are certain limitations in analyzing the power flow fault identification effect in micro electric networks only by the fault identification accuracy, so the power flow fault identification rate is experimented with, and the power flow fault identification rate of different methods is represented in Figure 4.

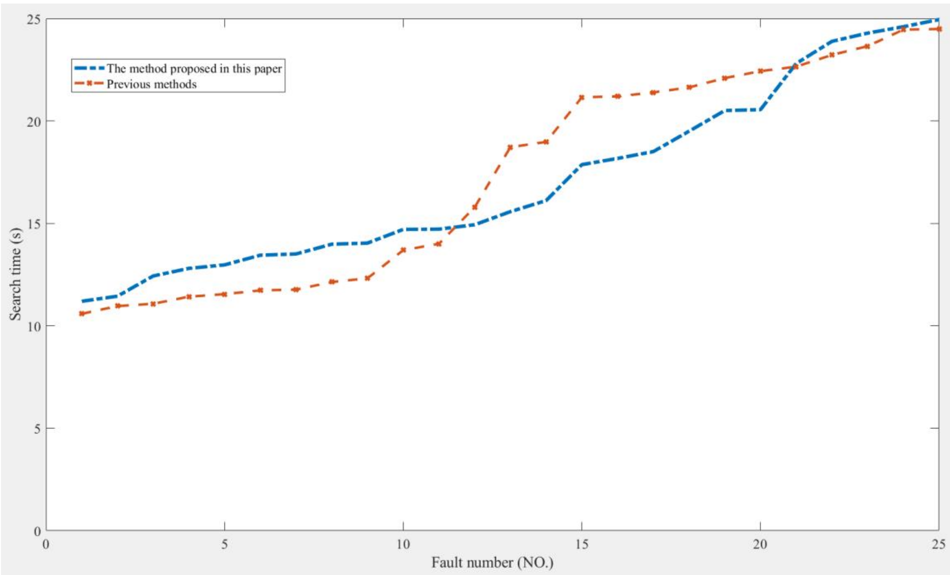

Figure 4. Comparison of Power Flow Fault Identification Rates of Different Methods

The analysis of Figure 4 shows that the proposed method's power flow fault identification rate is significantly higher than that of the other two methods. In many experiments, the proposed method's power flow fault identification rate is controlled at about 95%, which can ensure the accuracy of fault identification to a large extent. However, the other two methods have a low identification rate of power flow faults, which cannot meet the requirements of power flow fault identification in micro electric networks. Under the constraint of the same time, the visual search algorithm can improve the accuracy of fault identification in microgrids, which further confirms the effectiveness of the proposed method It shows that the method proposed in this paper has a strong ability to identify power flow faults in micro electric networks, and has high overall practicability. Figure 4 compares the proposed method's accuracy with the other two methods for power flow fault detection in micro electric networks [11].

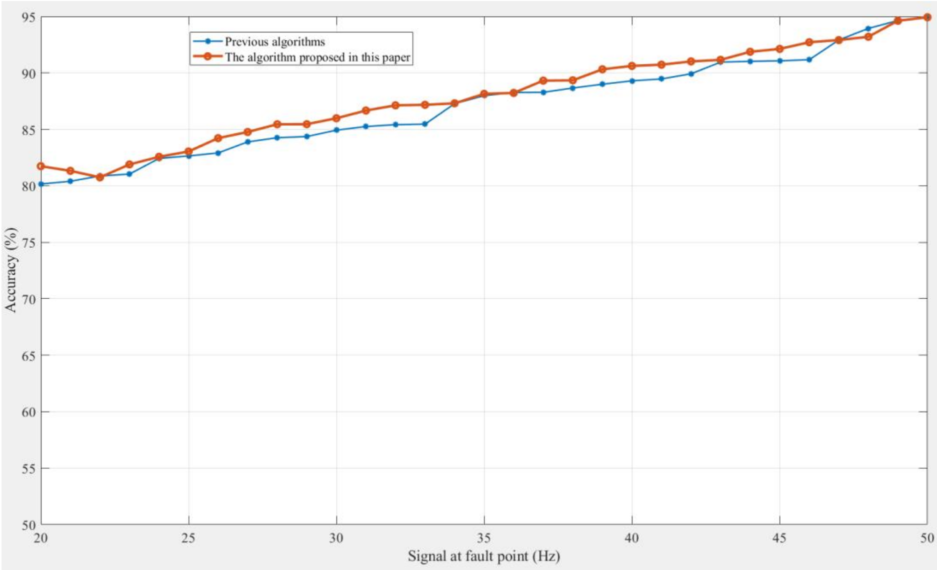

Figure 5. Accuracy of Power Flow Fault Identification

The analysis of Figure 5 shows that with the gradual increase of the data loss rate of the power grid, the accuracy of the power flow fault detection of the other two methods decreases greatly. However, the proposed method has better overall performance for power flow fault detection in micrograds, and with the gradual change of data loss ratio, it shows good fault detection performance. Therefore, the method proposed in this paper is very suitable for application to micro electric networks to identify power flow faults [12]. The results between the power flow search time and its fault search range are shown in Figure 6 below.

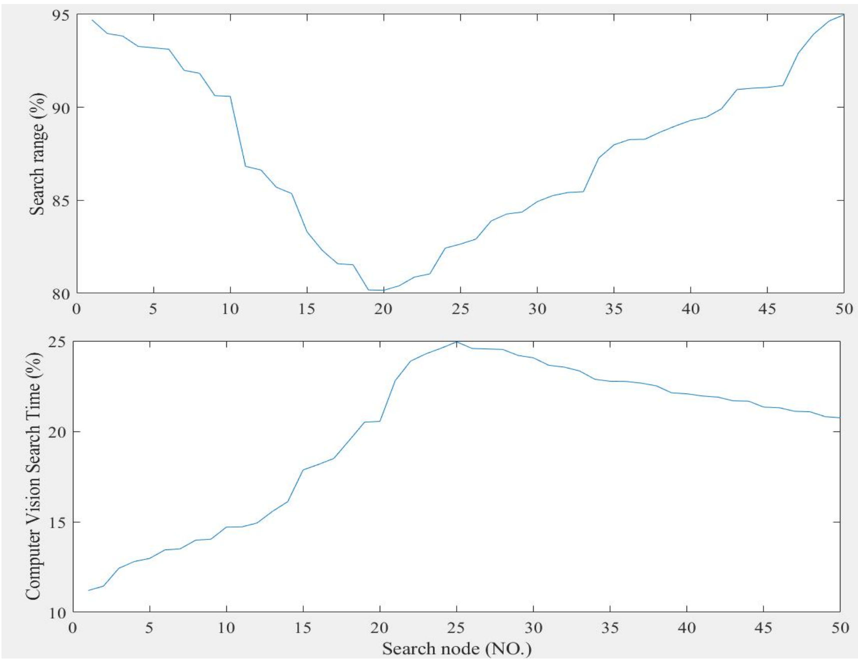

Figure 6. Comparison of Power Flow Fault Search Time and Range

Through the analysis of the computer vision search system, it can be found that there is a certain cross-relationship between the search time and the search range of the power flow fault, and when the search is carried out for a small number of devices, there is a negative change between the two, and when the number of searches increases, the change range shows a positive correlation, so the search process of the computer vision search system is relatively slow when a small amount of analysis is carried out, but a large number of searches can improve the search effect in the later stage.

6. Conclusion

Failure in the operation of the microgrid will not only affect the power supply of the power grid itself, but also affect the overall stable operation of the large power grid, and in severe cases, it is also prone to large-scale power outages of renewable energy grids. Therefore, this paper is used to identify power flow faults in microgrids based on a computer vision network search system, and to identify and deal with faults in the operation of renewable energy grids. In this paper, a power flow fault detection model based on a computational visual search algorithm is established, and fault detection is carried out by combining the status and signal of microgrid operation. The simulation results show that the computer vision search method has a strong ability to identify the overall power flow fault, improve the fault identification accuracy, by 80%~90%, and the search time is 10~20s, which greatly reduces the failure rate of the microgrid and ensures the effective operation of the renewable energy grid.

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