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Research on Fault Diagnosis Algorithm of Power Cable Based on Deep Learning

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Abstract: - The self-learning method is used to realize the online monitoring of optical cable after the fault occurs. According to the fuzzy characteristic of cable fault, a fuzzy basis function network is constructed which is similar to nonlinear function. Thus, the dynamic characteristics of the cable system are obtained. Then, this paper iterates each additional sample to realize the learning of the center point and radial of the network. A normal multivariable fuzzy distribution is used to determine the expected output of the new sample, and recursive operations are performed on the matrix and covariance matrix of the original sample. In this way, all failure probability distributions at the sampling points are obtained. Finally, the hardware module of the system is designed from two aspects: the distributed short-circuit fault collecting and processing equipment and the on-line temperature measuring equipment for grounding fault. In this way, the functions of software module reset, storage and communication are realized.

Keywords:Self-Learning Algorithm; Cable Comprehensive Diagnosis; Automatic Perception; Fuzzy Basis Function Network; Recursive Operation.

I. INTRODUCTION

Due to the complex structure of power cable system, its fault characteristics are also diverse. Some faults are random and fuzzy, which brings difficulty to the system fault detection. In reference [1], a new method of real-time monitoring using chaotic signals is adopted to solve the problems existing in power system. The fault diagnosis of a single wire rope is realized by using its unique autocorrelation characteristics. Then a large number of chaotic signals are used to detect the fault of complex cables. Literature [2] eliminate the errors caused by artificial influence, and Petri net is used for online fault diagnosis to enhance the adaptability to fuzzy information.

In the research of damage diagnosis based on partial discharge signals, how to effectively acquire and process the characteristic quantity of signals is the key to determine its performance [3]. Literature [4] intends to study the fractal properties, statistical properties, baud properties, Weibull parameters, image moment properties and texture properties. In these studies, the advantages of rich texture information, strong ability to resist external interference, strong resolution and high sensitivity have gradually attracted people's attention. However, PD of field monitoring cable has some problems, such as time and power consumption, less "skylight", and less collected discharge data. Moreover, the information contained in the obtained single-scale texture features is limited in scale and cannot reflect the multi-level information characteristics, which seriously restricts the identification results of fault categories. For this reason, many researchers began to study the use of multi-scale texture features to achieve target recognition and classification, and obtained good results. Literature [5] proposes a method based on image multi-scale binary model to solve the scene recognition problem under complex background. Literature [6] takes remote sensing images as the research object and proposes a method based on multi-scale gray co-occurrence matrix, which improves the overall recognition rate of images to 81.75%. Literature [7] intends to study an object skeleton recognition method based on multi-level structure to achieve high-probability capture of object contours. In literature [8], multi-scale gray image segmentation algorithm is

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used to achieve image recognition accuracy of more than 96%. The research shows that by increasing the feature dimension of the collected data. When the extracted texture feature dimension is larger, it contains more texture features. In order to express the information in the image more completely, more features must be extracted to construct a high-dimensional vector space. However, in the previous study, due to the influence of external disturbances, the above features decay, disappear or overlap, etc., making it difficult to obtain complete features, resulting in incomplete detection conclusions. Therefore, based on the self-learning method, this paper develops an intelligent detection system for cable integrated fault detection. Self-learning can not only adjust the parameters of the system by adjusting the known data to meet the needs of problem solving, but also enhance the adaptability to the environment by learning new data, which is of great significance for the research of intelligent detection.

II. DEPLOY A MONOLITHIC INTEGRATED CIRCUIT COMPUTER TO ACCOMPLISH ONGOING SUPERVISION OF ELECTRICAL CABLE ISOLATION INTEGRITY.

Because the laying distance of the cable is long and the direction is complex, there are many defects in the manual periodic inspection mode, inspection interval and inspection accuracy. The single-chip microcomputer can be used to detect the current of the cable ground wire in real time, arrange multiple measuring points along the cable, connect each measuring point with each measuring point, and conduct joint analysis of multiple measuring points in the entire system [9]. The insulation state of the cable is counted, so that the situation of leakage or insulation decline and the fault can be judged comprehensively. This method has the following characteristics: when the test device enters the power grid, there is no need to cut off the line or contact point, so that the transmission of the cable network will not be affected; The established test ground point is generally carried out in the place where the cable is connected, and it will only be opened when the monitoring is carried out, and it will be opened when the inspection is not carried out, so that the original working conditions and working characteristics will not be affected; For larger optical cables, multiple measuring points can be arranged on the optical cable, so that the fault point can be located more accurately. The system does not need to lay additional test cables, adopts wireless communication mode, and the measurement cables are not limited.

A. Working Principle

This paper introduces a new type of power cable insulation state detection system which is suitable for field measurement [10]. The handheld computer is used as the main control unit to monitor and coordinate the operation of the entire MCU. Using microcontroller as slave, the detection of line state is realized. During cable detection, the handheld computer first transmits a series of synchronization signals to the MCU to cooperate with the communication between the master and the slave, and then transmits the number of cables to be detected and the check signal of the starting cable of the child to the slave. After the detection is completed, the role of the host is to receive the cable detection information sent from the lower machine, and then process the information such as on, short, and broken cables, and perform troubleshooting. The schematic diagram of the system is shown in Figure 1(the picture is quoted in Machines 2023, 11(11), 985).

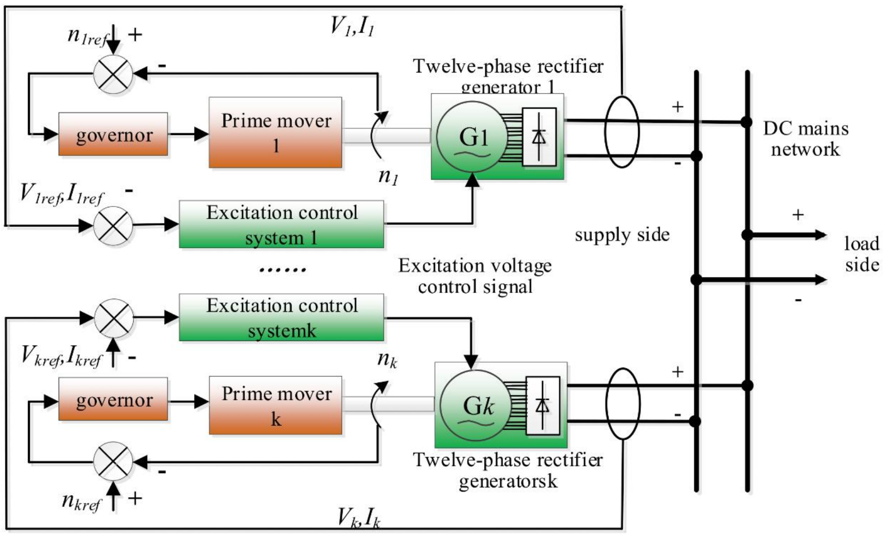

Fig.1 Schematic diagram of power cable fault monitoring system

B. Short Circuit Measurement

The micro processing device transmits the drive signal to the measured cable through adapter 1, and one end of the cable to be tested is in the suspended state. Under the control of MCU, the constant current source conducts the conduction of each cable in time, and the MCU reads the high and low states of the undriven core wire into the internal cache of MCU. If there is no short circuit between the cables and there is no loop in the power supply signal from adapter 1, the unenergized core wire should be low. The short-circuited cable cores can be determined by determining the high and low status of the cable core level [11]. For example, a high level is entered into a cable from the first core, and the child, after a tour, confirms that the fifth core is also high and the other core lines are low, which means that there is a short circuit between the fifth core and the first core.

C. On-off measurement

When working, the microprocessing unit transmits an excitation signal to the tested cable through an adapter1, and one end of the tested cable is short-circuited with a connector 2, that is, the connection between the two cables is conductive to each other, under the control of the PIC microprocessor, the constant current source opens each cable at a time. The high and low states of the cable's undriven core are read by the PIC microprocessor to the MCU's built-in cache via the PIC microprocessing system. When the disconnecting cable core is not used as the excitation wire, the core wire becomes low because there is no loop. When the disconnecting cable core wire is the excitation terminal, the other core wires should be low, and the cable core wire can be determined by determining the high or low level of the cable core wire to determine whether the cable core is disconnected or disconnected [12]. When the 1 core of the cable is input at high level, the sub-machine determines that the 5 core is low and the other core wires are high level after inspection, and the 5 core is disconnected. Or output 1 core to a high level, after detection, other core parts are low, then 1 core disconnected.

D. Determination of through point and break point

If a cable is disconnected, how to locate it is briefly described in the following sections. During the detection process, the end of the disconnected failed cable is connected, and then the detector is moved along the cable, and the detector can make a sound [13]. Once at the fork, the sound will be cut off and there will be no sound on the detectors, so they can determine the exact location of the fork. In the detection multi-core cable, if one cable fails to disconnect, the remaining core wires should be grounded as much as possible to reduce the interference of the distribution capacitor on the cable, so as to achieve better detection results.

III. CONSTRUCTION OF AN ONLINE MONITORING FRAMEWORK FOR POWER CABLE INSULATION DEFICIENCIES, EMPLOYING A SOLITARY INTEGRATED CIRCUIT MICROPROCESSOR.

A. Hardware Architecture

This paper introduces the power line monitoring and alarm system based on C8051 microcontroller. The system consists of two main components: one is hardware, the other is software. A block diagram of the hardware component of the solution is shown in Figure 2 (image cited from Sensors 2020, 20(18), 5273).

The hardware design of the system mainly includes three modules: host, main control machine and temperature collector. From the overall level, the system can be divided into three levels: computer as the core of the host management, and single-chip microcomputer as the core of the machine control layer, and collector test layer. Figure 2 shows the composition of the system. This computer to read the temperature information regularly. When the master computer receives the instruction, it uploads the data saved in the SRAM previously read from the collector to the host computer [14]. When the host completes the transmission, the host will read the temperature information to the collector, the collector received the instruction, the information stored in the SRAM to the host. The host accepts the original data in the corresponding memory and modifies it. In the communication gap, the collecting device will continuously read the recent temperature data at the cable connection for immediate reading by the master controller. The system adopts a complete set of communication protocols and adopts a variety of checking methods to ensure the reliability of the system during transmission.

1) Upper computer

The upper computer can be controlled by a high-performance computer to ensure normal operation 24 hours a day. The upper computer communicates with multiple master computers through PC, receives temperature data of each node, and outputs data in graphical forms such as reports and curves. When a set condition is exceeded, a visual alarm and an audible alarm appear immediately.

2) Primary Controller

The lower computer adopts C8051 single chip microcomputer, which is composed of single chip microcomputer, memory and communication interface, and is connected to the upper computer through RS485 communication interface, GPRS and public network. The task of the host is to patrol and record the temperature values collected by the collector.

3) Collector

The acquisition device includes C8051 series chip, temperature detection channel selection circuit, communication circuit, memory and so on. Through the selection of the temperature measurement path, the single chip microcomputer detects the temperature of each temperature sensor, and stores the collected temperature information in the external SRAM. Once the host needs it, the data can be extracted at any time and transmitted to the host.

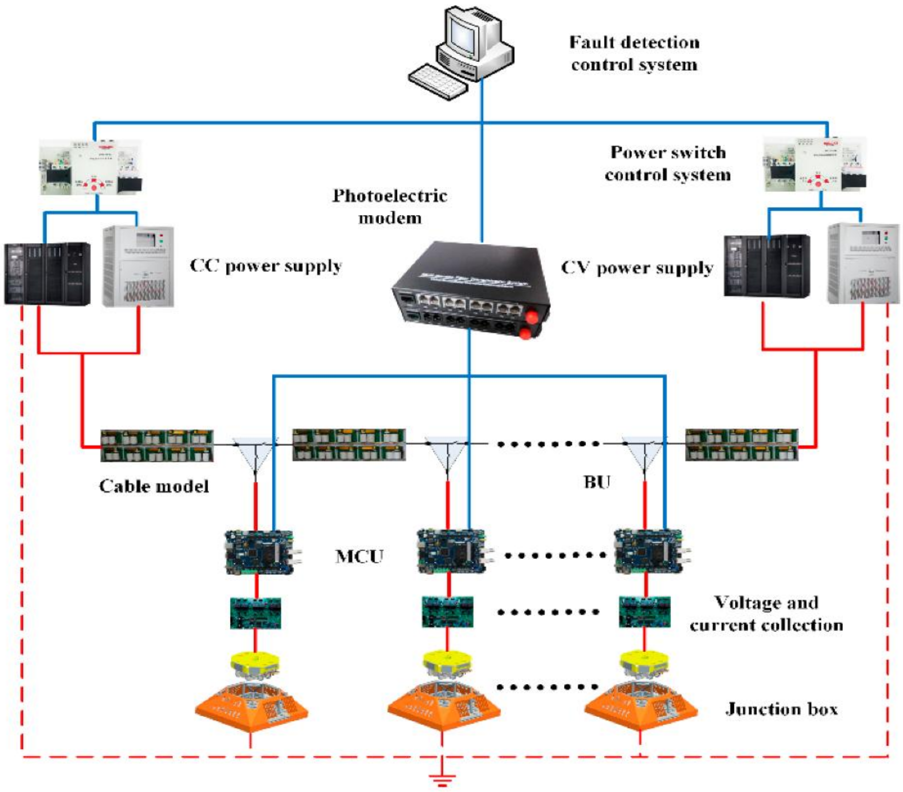

Fig.2 Hardware architecture of power cable fault monitoring system

4) Sensors

The device uses the new digital temperature control element DS1820 produced by DALLAS Company in the United States, which can accurately measure the temperature of cable joints and other parts under the environment of -55-125 ° C, precisely controlled at -55-125 ° C, and precisely controlled at ±0.5 ° C. The digital temperature sensor uses a half-duplex data communication interface, the master station inputs the ID code and instruction word into it, and puts its digital temperature value [15]. The lower computer is mainly responsible for real-time acquisition of various parameters of each measuring point. After simple processing, the serial number of each measuring point and related parameters are sent to the upper computer through the serial port. The host computer mainly monitors each master station, receives the information sent by each master station from the master station, and monitors and displays it in real time using friendly man-machine interface on the Windows platform.

B. Software Architecture

VB6.0 is used to write A/D and PC communication, Kingview is used for MMI configuration software, and DDE and VB are used for data interaction. The system also includes the main line temperature monitoring screen, alarm screen, history curve, real-time curve and "help" button and other functions [16]. The operating status interface of the system has two functions: regional wiring and electronic wiring. The system uses the circuit diagram of a substation as the main screen to monitor the circuit. These cables are numbered to indicate the temperature of the corresponding cable node. If the temperature at one of the cable connections is outside the specified range, the device will sound an alarm and display different colors according to different temperature displays to remind the operator to do the right thing. Five keys are set on the main screen, and the corresponding screen window will be displayed after entering the history curve, real-time curve, alarm window and help button. The system uses a communication mode based on asynchronous serial communication, and communicates with the host computer. The device realizes off-line configuration and real-time monitoring, and provides a friendly man-machine interface [17]. In the online monitoring, also set a cable channel status and temperature measurement point distribution map, it will be the specific location of each node and the current temperature data are visually displayed, the general state, the node is green, once the temperature of a node exceeds a certain range, it will turn red, thus prompting overheating alarm. When the temperature of the connection is close to the setting, the connection will appear yellow. Thus, the optical cable in the actual line is dynamically illustrated.

The system includes distributed short-circuit fault acquisition and processing module, distributed grounding fault and online temperature measurement acquisition and processing module, background integrated management module. 1) Distributed short-circuit fault collection module is used to collect key parameters of the line; The analysis and analysis of the data, including the analysis of the current, load current and current, as well as the fault diagnosis associated with the current state, are recorded and uploaded. 2) The temperature of the distribution line are measured and analyzed during the operation of the temperature measurement data acquisition system of the distribution line. When short circuit occurs in the line, the zero sequence current are connected with the characteristics of the line, and the real-time monitoring of the line is realized. You can check the cable temperature 24 hours a day by checking the cable online. Once the maximum threshold is found, it should be reported in time. Temperature measuring devices are installed at each 100 m cable connection point. 3) The integrated management module of the integration back end can effectively manage the topology of the cable according to the above failure determination logic. At the same time, the failure location is displayed in real time through GIS technology and provides reference for the decision-making of relevant departments (Figure 3 is quoted in the Research on Primary Frequency Regulation Control Strategy of Wind-thermal Power Coordination).

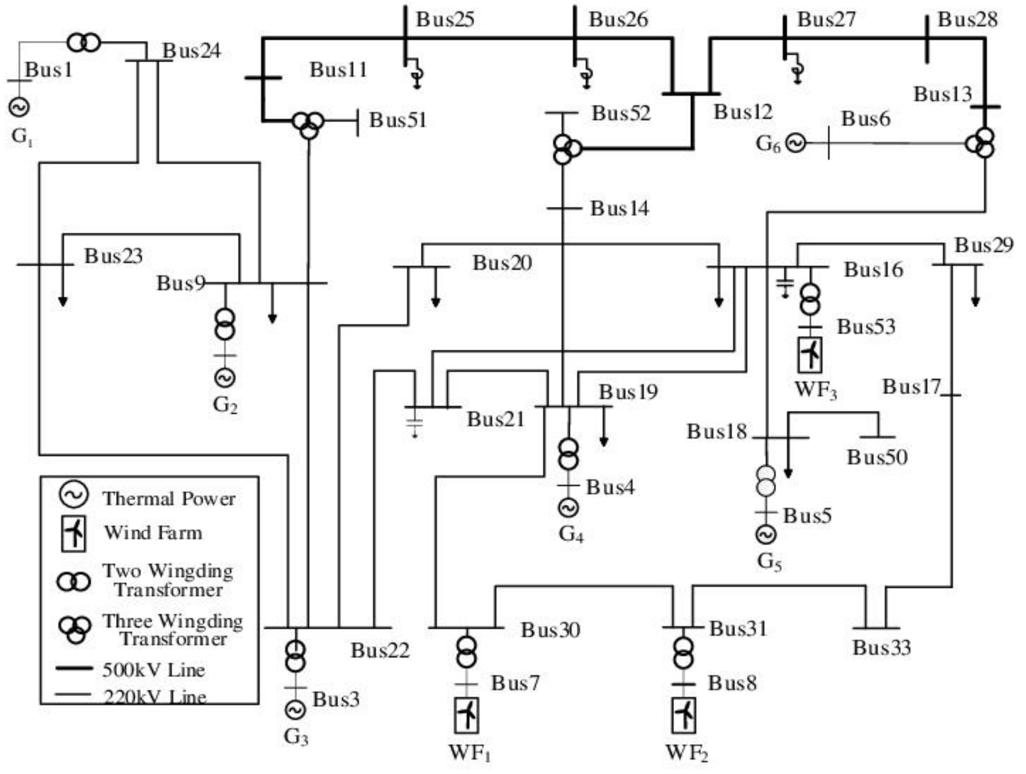

Fig.3 Networking diagram of the power cable system

IV. FUZZY BASIS FUNCTION SELF-LEARNING FAULT DIAGNOSIS UNDER THE NEW SAMPLE

In order to prevent the phenomenon of "sudden forgetting", the training sample set must contain all old samples and new samples. But as the experimental data increases, so does the difficulty of training.

A. Center of circle and radial learning of Fuzzy base function guide network

The algorithm takes the basic neural network as the initial core, and carries out a cycle for each new sampling point added, which can not only reduce the old search rate, but also prevent the occurrence of relearning, so as to improve the efficiency of learning, and meet the requirements of unrecognized [18]. In the i network unit, the new M element of the center vector can be obtained recursively by the following formula:

$$z_{M_i+1,ij} = \begin{cases} z_{M_{i,ij}} + \gamma(u_{M_i+1,j} - z_{M_{i,ij}}), u_{M_i+1} \in Z_i \\ z_{M_{i,ij}} + \delta(u_{M_i+1,j} - z_{M_{i,ij}}), u_{M_i+1} \notin Z_i \end{cases} \quad (1)$$

γ and δ represent the learning rates of winning and non-winning units in the self-learning algorithm respectively, and $0 < \gamma < 1, 0 < \delta < 1, Z_i$ is the data type represented by the i network unit. Then the new radius calculation formula of the first fuzzy basis function network unit $z_{M_i+1,ij} - z_{M_i,ij}$ is as follows:

$$\varepsilon_{M_i+1,ij} = \max_{i \neq j} \left(z_{M_i+1,ij} - z_{M_i,ij} \right)^2 / L \quad (2)$$

B. Determination of ideal output of new samples

A weighted mean algorithm with neglect coefficient is proposed. The weighted average method with forgetting factor is introduced. Assuming that such failures have a weighted mean of Q sampling points, the expression is as follows:

$$u_Q = \frac{\sum_{i=1}^{Q} \eta^{Q-1} U_i}{\sum_{i=1}^{Q} \eta^{Q-1}} = \frac{1-\eta}{1-\eta^Q} \left(\sum_{i=1}^{Q} \eta^{Q-i} U_i \right) \quad (3)$$

$U_i (i = 1, 2, \cdots, Q)$ is the sample vector, Q is the number of samples, η is the forgetting factor, $\eta \in (0.95, 1)$. Then the weighted covariance matrix is expressed as:

$$\sum_Q = \frac{\sum_{i=1}^{Q} \eta^{Q-i} (U_i - u_Q)(U_i - u_Q)^T}{\sum_{i=1}^{Q} \eta^{Q-1}} \quad (4)$$

For a given sample U_j, its expected output can be obtained through the following normal types of multivariate fuzzy allocation:

$$\zeta_j = \exp\left(-\frac{1}{r} s_j^2 \right) \quad (5)$$

$$s_j = \left(U_j - u_Q \right)^T \sum_Q^{-1} (U_j - u_Q) \quad (6)$$

In the formula, s_j represents the distance between U_j and the fault class center u_Q, and r is a normal number, which can adjust the ideal output of the sample. In general, the possible output of the sample farthest from u_Q is $\zeta_j = 0.5$.

C. Recursive operation of sample mean and covariance matrix

In order to directly obtain samples with missing factors, it is necessary to know all the failed samples, which requires a lot of calculation time [19]. Therefore, an iterative method for solving the problem is given. Suppose the mean and covariance matrices as Q_n and $\sum_n$, respectively. After adding U_{n+1} new samples, there are:

$$U_{n+1} = \frac{1-\eta}{1-\eta^{n+1}} \left(\sum_{i=1}^{n+1} \eta^{n+1-i} U_i \right) = (1 - \xi_{n+1}) Q_n + \xi_{n+1} \quad (7)$$

$$\sum_{n+1} = (Q_n - U_{n+1})(Q_n - U_{n+1})^T \quad (8)$$

The following matrix inversion formula is used:

$$(a+bc)^{-1} = a^{-1} - a^{-1}b(I + Za^{-1}b^{-1})Za^{-1} \quad (9)$$

Take $a = \sum_n, b = \xi_{n+1}(Q_n - U_{n+1}), Z = (Q_n - U_{n+1})$, so there is:

$$\sum_{n+1}^{1} = (Q_n - U_{n+1})^T \sum_{n}^{1} (Q_n - U_{n+1}) \quad (10)$$

Formulas (10)~(13) can be used to complete the recursive operation of the mean Q_{n+1} of the forgetting factor sample and the covariance matrix $\sum_{n+1}$, obtain all the fault possibility distribution information in the sample, and form the target output of the new sample, so as to realize the fault perception.

V. CLASSIFICATION RESULTS

A. *Comparison of texture characteristics and performance*

This project intends to collect 600 images, 50 images each, 3 groups of 3 different types of images. The self-learning algorithm is shown in Table 1 [20]. The typical PRPD spectral features of sample a_3, b_3, c_3 were taken as test samples, and there were 200 test samples in total.

Table 1. Training samples and test samples

sample type	Sample source	Sample size	Sample type	Sample source	Sample size
Training sample	a_1, a_2	100	Test sample	a_3	50
	b_1, b_2	100		b_3	50
	c_1, c_2	100		c_3	50
	d_1, d_2	100		d_3	50

The number of decision trees n_{tree} and the number of $t_r = \sqrt{t_{all}}$. The model error rate and class error rate are used as evaluation criteria [21]. This paper also puts forward 7 solutions. Here, schemes 1 through 4 are single feature Spaces. Scheme 5-7 is a multi-scale feature space. Figure 4 shows the differentof n_{tree} . This isthe n_{tree} selection, thereby reducing the recognition rate of the classifier, or producing excessive learning effects [22]. The accuracy of multi-scale structure stabilization is better than that of single scale structure.

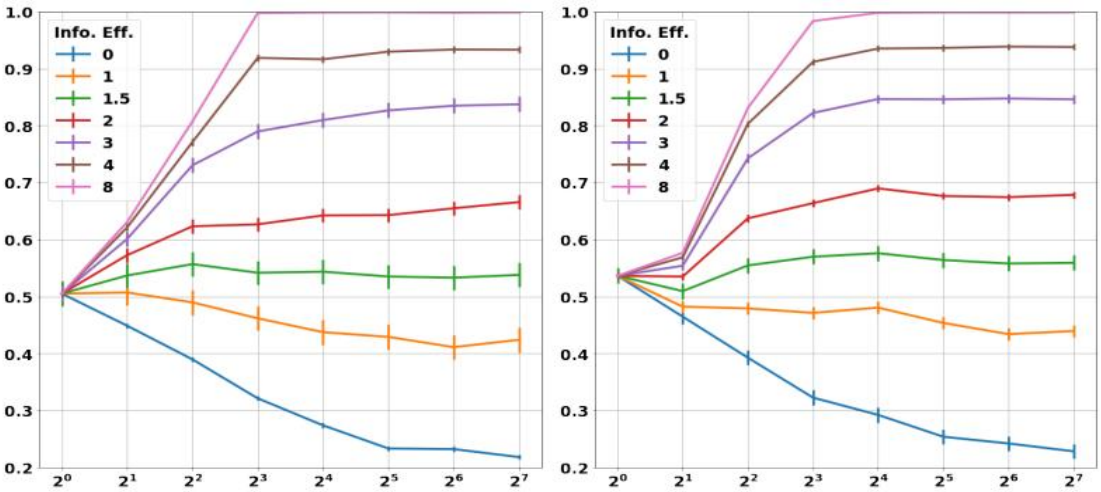

Fig.4 Error rate of self-learning model

Figure 5 shows the recognition accuracy of n_{tree} is 50,100,200. There is no significant difference between the recognition accuracy of multi-scale structure and single-scale structure in stage $n_{tree} = 50$. The correct rate of

Plan 5 and Plan 7 at $n_{tree} = 100$ is 97.33% and 98.38%, which is significantly higher than that of Plan 3 and Plan 4, while the correct rate of plan 1, Plan 2 and Plan 6 is 96.80%. In stage $n_{tree} = 200$.

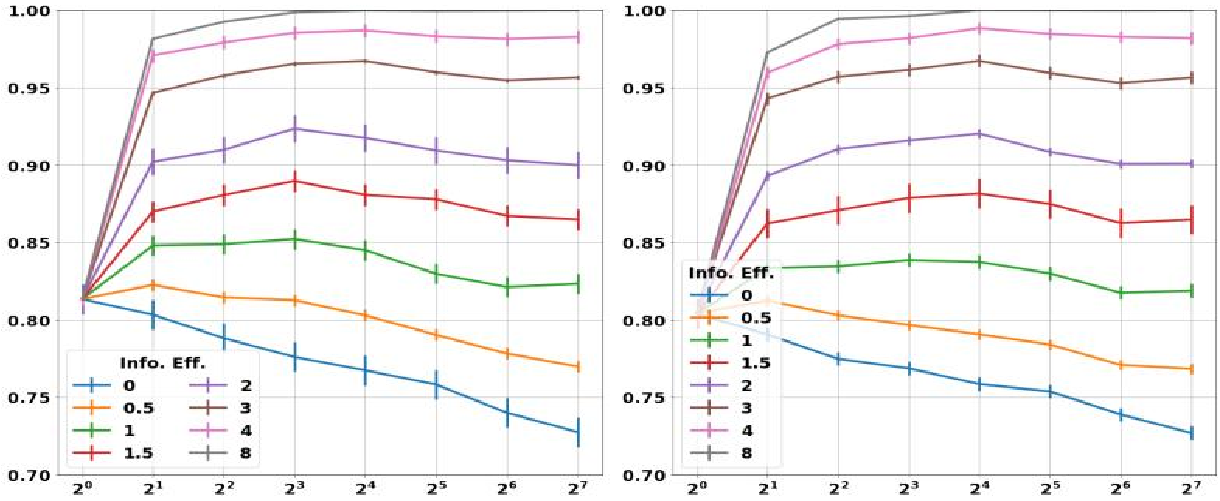

Fig.5 Classification accuracy of self-learning model

Figure 5 shows the self-learning recognition of individual defects. Therefore, this paper proposes A fuzzy matrix when n_{tree} is 50,100,200. The fuzzy matrix is used to distinguish the classifier and compare it with the real data [23]. In addition, the misclassification of 2 numbers is mainly 4 numbers, and the error number of 4 numbers is mainly 2 numbers. This is because number 2 and number 4 correspond to ring scratch defects and air gap defects respectively. Air gap defects are caused by cutting depth and have a similar discharge mechanism with ring scratch. Therefore, there is a certain deviation in the classification of air gap and ring scratch defects.

B. Gini Index was used to rank attribute importance

gini index is the change of gini impurity degree when the same attribute is divided. The greater the value, the higher the importance. Use equation (10) to calculate the gini index.

$$\begin{cases} gini(M) = 1 - \sum_{i=1}^{n_s} g_i^2 \\ gini(M, A) = \sum_{j=1}^{m} \frac{|M_j|}{|M|} gini(M_j) \end{cases} \tag{11}$$

M_j is the j of the selected sample. In this paper, the number of a tree is selected as $n_{tree} = 200$, and its partition mode is determined according to the best characteristics of this node, because the best characteristics obtained by it will vary greatly under different constraints, so this paper will use the gini index to sort the 164 feature quantities in 7. The rate of decline of the gini index represents the degree to which the impurity of gini decreases after the substitution of the eigenvector, and a larger value indicates the importance of the variable. Thirty-three feature quantities whose decline rate is greater than 0.01 with gini index are selected for secondary training [24]. Figure 6 illustrates the discrepancy rate and identification precision between strategies 7 and 8. Model 8's predictive efficiency stands at half the peak level, attaining a figure of 0.0289, thus falling short when compared to Model 7's performance.When n_{tree}=50,100,200, scheme 8 has better recognition accuracy than 7.

The feature space optimized by gini index reduces the parameter n_{tree} in the learning process by 50%, and the model error rate by 2.87%.

C. Comparison of recognition algorithms

The recognition accuracy of multi-scale texture is studied by using BP neural network, SVM and self-learning method. The non-GINi index optimal multi-scale texture characteristics were used as the input for identification, and the accuracy of each identification method was shown in Table 2. The used for image classification. The accuracy of each identification method is shown in Table 3.

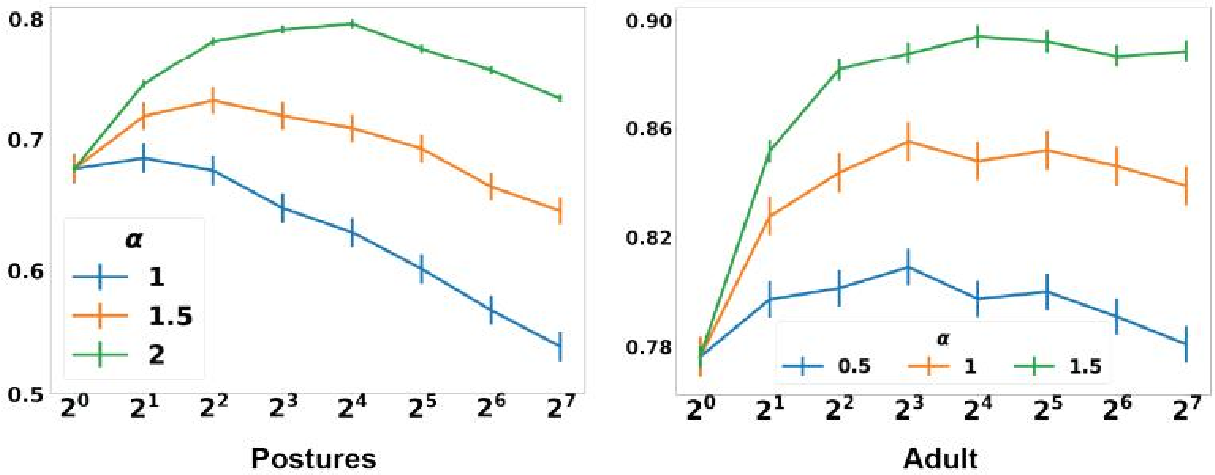

Fig.6 Comparison of self-learning model performance between scheme 7 and Scheme 8

Table 2. Comparison of algorithm performance before optimizing features

algorithm		BP neural network	Support vector machine	self-learning
Accuracy rate / %	Tip defect	90.48	94.7	100
	Looped scratch defect	86.28	90.48	96.8
	Metal particle defect	88.38	92.6	100
	Air gap defect	84.17	88.38	96.8
Time consuming/s		125.45	42.73	3.33

Table 3. Comparison of algorithm performance after optimized features

algorithm		BP neural network	Support vector machine	self-learning
Accuracy rate / %	Tip defect	96.8	96.8	100
	Looped scratch defect	92.6	94.7	100
	Metal particle defect	94.7	96.8	100
	Air gap defect	92.6	92.6	96.8
Time consuming/s		35.76	20	1.21

Power cable fault diagnosis technology is the key link to ensure the stable operation of power grid and improve the reliability of power supply. With the continuous expansion and complexity of power system, the types and causes of cable faults are increasingly diversified, and the traditional fault diagnosis methods are difficult to meet the needs of modern power system. It is very important to develop efficient and accurate power cable fault diagnosis technology.

At present, the power cable fault diagnosis technology mainly includes the method based on physical model, the method based on signal processing and the method based on artificial intelligence. The physical model-based method relies on the electrical characteristics and fault mechanism of the cable, and analyzes and locates the fault by establishing a mathematical model. This method has high accuracy in theory, but it is limited by the complexity of cable model and the uncertainty of parameters in practical application. The method based on signal processing can diagnose the fault by analyzing the characteristics of the electrical signal generated by the cable fault, such as time-domain waveform analysis and frequency-domain analysis. These methods have high requirements for signal processing and feature extraction, and are easily affected by noise and interference.

In recent years, the power cable fault diagnosis technology based on artificial intelligence has gradually become a research hotspot. Among them, deep learning, as an important branch of artificial intelligence, has shown great potential in power cable fault diagnosis. Deep learning can automatically learn and extract data features by constructing multi-layer neural network models, which can deal with complex nonlinear problems and has strong adaptive ability and generalization ability. In power cable fault diagnosis, deep learning can use the time domain, frequency domain or time-frequency domain features of fault signals to realize automatic fault identification and classification through the trained model.

Compared with traditional fault diagnosis methods, the power cable fault diagnosis technology based on deep learning has the following advantages:

High accuracy: The deep learning model can learn the deep characteristics of the fault signal and improve the accuracy of fault diagnosis. Strong adaptive ability: Deep learning models can automatically adapt to different types and causes of cable failures without manually adjusting model parameters. Fast processing speed: Through optimization algorithms and parallel processing techniques, deep learning can achieve real-time or near-real-time fault diagnosis. Strong generalization ability: Deep learning models can maintain good diagnostic performance in different data sets and application scenarios.

This shows great potential when dealing with complex image recognition problems, especially in application scenarios that require fast and accurate recognition.

VI. FORECAST DEVELOPMENT

With the rapid development of the power industry and the continuous progress of intelligent technology, power cable fault diagnosis technology will also usher in new development opportunities. In the future, the power cable fault diagnosis algorithm based on deep learning will be more mature and achieve a higher level of automation and intelligence. The continuous development of deep learning technology will provide more powerful support for power cable fault diagnosis. With the continuous improvement of deep learning algorithms and the improvement of computing power, more complex and accurate fault diagnosis models can be built in the future to achieve more accurate identification and positioning of cable faults. At the same time, deep learning technology can also be applied to fault prediction and health management, to detect potential faults in advance and take corresponding measures to further improve the stability and reliability of the power system. The continuous progress of sensor technology will provide more abundant data sources for power cable fault diagnosis. In the future, advanced sensor technology can be used to monitor power cables in real time to obtain more detailed and accurate fault information. These data can provide more sufficient input for fault diagnosis algorithm and improve the accuracy and efficiency of fault diagnosis. The continuous development of artificial intelligence technology will provide a wider application prospect for power cable fault diagnosis. Artificial intelligence technology can be applied to all aspects of power cable fault diagnosis to achieve full automation and intelligence of fault diagnosis. At the same time, artificial intelligence technology can also be applied to fault data mining and analysis, find new fault characteristics and rules, and provide more valuable reference information for fault diagnosis.

VII. CONCLUSION

This project has successfully developed a power cable fault diagnosis system based on deep learning, which realizes a comprehensive and accurate diagnosis of cable faults through self-learning method, and provides a strong guarantee for the stable operation of the power system. The development of the system not only improves the accuracy of fault location, but also can react quickly after the accident and work out the corresponding countermeasures, so as to effectively reduce the significant economic losses. With the continuous progress of science and technology and the rapid development of the power industry, power cable as an important part of the power system, its security and stability have been paid more and more attention. Because of the complexity of power cable system structure and the diversity of fault characteristics, the traditional fault diagnosis methods are often difficult to meet the actual needs. It is of great practical significance and application value to develop an efficient and accurate power cable fault diagnosis method. In this paper, based on deep learning technology, fuzzy basis function network and recursive operation are used to realize automatic perception and comprehensive diagnosis of power cable faults. The system can not only deal with complex nonlinear problems, but also learn new data features adaptively and improve the adaptability to the environment. Through a large number of experiments, the system has a high diagnostic accuracy and robustness, and can meet the needs of practical applications. In terms of hardware, a distributed short-circuit fault acquisition and processing device and an on-line temperature measuring device for grounding fault are designed to realize real-time monitoring of cable status. In the aspect of software, the functions of reset, storage and communication are realized to ensure the stability and reliability of the system. With the continuous development of deep learning technology, sensor technology and artificial intelligence technology, power cable fault diagnosis technology will usher in new development opportunities. In the future, the algorithm model can be further optimized to improve the accuracy and efficiency of fault diagnosis. It is possible to explore the application of more advanced technologies in the field of fault diagnosis, such as transfer learning, incremental learning, etc., to cope with the changing fault characteristics and environmental conditions. It can also strengthen the cross-integration with other related fields and promote the innovative development of power cable fault diagnosis technology. The power cable fault diagnosis system based on deep learning in this project provides a strong guarantee for the safe and stable operation of the power system. In the future, with the continuous progress of technology and the continuous improvement of application demand, the system will continue to play an important role and promote the continuous development of power cable fault diagnosis technology.

REFERENCES

[1] Wang, M. H., Lu, S. D., & Liao, R. M. (2021). Fault diagnosis for power cables based on convolutional neural network with chaotic system and discrete wavelet transform. IEEE Transactions on Power Delivery, 37(1), 582-590.
[2] Furse, C. M., Kafal, M., Razzaghi, R., & Shin, Y. J. (2020). Fault diagnosis for electrical systems and power networks: A review. IEEE Sensors Journal, 21(2), 888-906.
[3] Hua, X., Wang, L., & Zhang, Y. (2021). Analysis and diagnosis of shielded cable faults based on finite-element method and time-reversal time-frequency domain reflectometry. IEEE Transactions on Industrial Electronics, 69(4), 4205-4214.
[4] Sian, H. W., Kuo, C. C., Der Lu, S., & Wang, M. H. (2023). A novel fault diagnosis method of power cable based on convolutional probabilistic neural network with discrete wavelet transform and symmetrized dot pattern. IET Science, Measurement & Technology, 17(2), 58-70.
[5] Wang, X., Liu, E., & Zhang, B. (2021). Reflectometry-based cable insulation aging diagnosis and prognosis. IEEE Transactions on Industrial Electronics, 69(4), 4148-4157.
[6] Lee, H. M., Lee, G. S., Kwon, G. Y., Bang, S. S., & Shin, Y. J. (2020). Industrial applications of cable diagnostics and monitoring cables via time–frequency domain reflectometry. IEEE Sensors Journal, 21(2), 1082-1091.
[7] Saad, M. H., & Said, A. (2023). Machine learning-based fault diagnosis for research nuclear reactor medium voltage power cables in fraction Fourier domain. Electrical Engineering, 105(1), 25-42.
[8] Ren, Z., & Zhang, Y. (2020). Energy entropy and particle swarm optimization BP neural network of fault diagnosis techniques of coal mine cable. Journal of System Simulation, 27(5), 1044-1049.
[9] Li, S., Cao, B., Li, J., Cui, Y., Kang, Y., & Wu, G. (2023). Review of condition monitoring and defect inspection methods for composited cable terminals. High Voltage, 8(3), 431-444.
[10] Wu, Z., Zhou, L., Lin, T., Zhou, X., Wang, D., Gao, S., & Jiang, F. (2020). A new testing method for the diagnosis of winding faults in transformer. IEEE Transactions on Instrumentation and Measurement, 69(11), 9203-9214.
[11] Gulski, E., & Jongen, R. (2021). Condition based maintenance of transmission power cables. IEEE Transactions on Power Delivery, 37(3), 1588-1597.
[12] Wong, S. Y., Choe, C. W. C., Goh, H. H., Low, Y. W., Cheah, D. Y. S., & Pang, C. (2021). Power transmission line fault detection and diagnosis based on artificial intelligence approach and its development in uav: A review. Arabian Journal for Science and Engineering, 46(10), 9305-9331.
[13] Aizpurua, J. I., Stewart, B. G., McArthur, S. D., Jajware, N., Kearns, M., Garro, U., ... & Mendicute, M. (2020). A diagnostics framework for underground power cables lifetime estimation under uncertainty. IEEE Transactions on Power Delivery, 36(4), 2014-2024.
[14] Chi, P., Zhang, Z., Liang, R., Hu, Y., Ni, K., & Li, W. (2022). A fault diagnosis method of double-layer LSTM for 10 kV single-core cable based on multiple observable electrical quantities. Electrical Engineering, 104(2), 603-614.
[15] Xia, C., Ren, M., Wang, B., Dong, M., Xu, G., Xie, J., & Zhang, C. (2021). Infrared thermography-based diagnostics on power equipment: State-of-the-art. High Voltage, 6(3), 387-407.
[16] Meradi, S., Benmansour, K., & Laribi, S. (2023). Failure analysis of medium voltage underground power Câbles based on voltage measurements. Journal of Failure Analysis and Prevention, 23(5), 1860-1868.
[17] Lee, C. K., & Shin, Y. J. (2020). Detection and assessment of I&C cable faults using time–frequency R-CNN-based reflectometry. IEEE transactions on Industrial Electronics, 68(2), 1581-1590.
[18] Fahim, S. R., Sarker, S. K., Muyeen, S. M., Sheikh, M. R. I., Das, S. K., & Simoes, M. (2021). A robust self-attentive capsule network for fault diagnosis of series-compensated transmission line. IEEE Transactions on Power Delivery, 36(6), 3846-3857.
[19] Furse, C., Kafal, M., Razzaghi, R., & Shin, Y. J. (2020). Special issue on embedded sensors for fault diagnosis in electrical wiring interconnection systems, power grids, structural cables, pipelines, and electrical machines. IEEE Sensors Journal, 21(2), 886-887.
[20] Shi, X., Liu, Y., Xu, X., & Jing, T. (2020). Online detection of aircraft ARINC bus cable fault based on SSTDR. IEEE Systems Journal, 15(2), 2482-2491.
[21] Mitiche, I., Nesbitt, A., Conner, S., Boreham, P., & Morison, G. (2020). 1D-CNN based real-time fault detection system for power asset diagnostics. IET Generation, Transmission & Distribution, 14(24), 5766-5773.
[22] Rajpoot, S. C., Pandey, C., Rajpoot, P. S., Singhai, S. K., & Sethy, P. K. (2021). A dynamic-SUGPDS model for faults detection and isolation of underground power cable based on detection and isolation algorithm and smart sensors. Journal of Electrical Engineering & Technology, 16(4), 1799-1819.
[23] Davari, N., Akbarizadeh, G., & Mashhour, E. (2020). Intelligent diagnosis of incipient fault in power distribution lines based on corona detection in UV-visible videos. IEEE Transactions on Power Delivery, 36(6), 3640-3648.
[24] Tang, H., Lu, S., Qian, G., Ding, J., Liu, Y., & Wang, Q. (2020). IoT-based signal enhancement and compression method for efficient motor bearing fault diagnosis. IEEE Sensors Journal, 21(2), 1820-1828.