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Reinforcement Learning-based Optimization Method for Hidden Danger Early Warning and Fault Location of Distribution Network Cables in Smart Power System Environment

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SUMMARY: *With the growing demand for electricity in people's daily production and life, the density and complexity of the distribution network is also increasing, and line faults in the distribution network will affect the normal power supply of the distribution network system, thus affecting people's normal production and life, and causing huge economic losses. This paper collects the data of distribution network cable lines, and determines whether the distribution network is discharging hidden danger by analyzing the relationship between the discharge current and the number of discharges. Use the double-ended traveling wave method to accurately locate the cable faults and construct the distribution network cable hidden danger early warning model construction. Aiming at the problem of complex fault situations in the field operation of power equipment, the reinforcement learning method is proposed to further optimize fault location. The fastest response time, the slowest response time and the average response time of the proposed early warning method in this paper are 0.3569s, 0.7259s and 0.5328s, respectively, which are better than the comparison method. In fault localization, the five differential currents are basically stabilized near 0 at the beginning stage of wave recording, and at about 190-205ms* ΔI_3, ΔI_5 *mutated,* ΔI_3 *mutated close to 7000A, and it is judged that the B-phase and the mid-point area of the high and low valves have occurred a After the field test, the actual fault is consistent with the analysis results.*

KEYWORDS: *double-ended traveling wave method; cable hazard warning model; reinforcement learning; fault localization*

1 Introduction

According to the International Energy Agency (IEA), electricity is a key component of energy consumption in all countries, and the development of smart power systems is becoming the key to realizing clean, efficient as well as sustainable energy [1-3]. In the smart power system, the potential hazard warning and fault location technology of distribution cables as an important component plays an important role in monitoring, optimizing and securing the operation of the power grid [4]. According to the IEA report, the application of fault location technology can provide accurate assessment, fault diagnosis and repair guidance for the power grid, as well as load forecasting and optimization to achieve efficient operation of the power grid and energy utilization efficiency [5-7]. At the same time, the hidden danger warning technology analyzes the security of future operation scenarios of distribution network cables

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in advance, identifies insecurity risks and provides guidance information for prevention and control decision-making, which is an effective means to ensure the safe and stable operation of the type power system [8, 9].

Distribution cables have become more and more important in the process of power grid development, especially in modern urban power grids, high-voltage cables are equivalent to a city transmission junction “artery”, so many scholars are committed to the study of the reliability of power cables [10-12]. Considering that the main cause of distribution cable failure is the complicated external environment, it is necessary to carry out rapid and accurate early warning based on the hidden dangers existing in the external environment of the distribution cable, so as to take timely and targeted treatment means to minimize the potential failure risk of power cables [13-15]. Literature [16] combines Monte Carlo simulation with cable system modeling to capture the risk of cable aging during emergencies over a multi-year period, including cable short-circuit failures, as well as failures such as cable fires and cable breaks due to insulation aging, and even larger safety incidents. Literature [17] developed a method for calculating the total duration of anomalous current operation and utilized this information for early warning of potential faults, and established a current-carrying state assessment method and an early fault warning model based on the theoretical relationship between temperature and current. Literature [18] developed a method for power cable state identification based on a deep learning model combined with an infrared image system for early warning of cable risks in distribution networks. The application of reinforcement learning (RL) algorithms can better support the study of power cable fault risk in complex environments [19]. Literature [20] model-free control approach based on reinforcement learning for reclosing control to mitigate transient overvoltages and cable faults in distribution systems with degraded insulation. Literature [21] describes the application of Deep Reinforcement Learning (DRL) in power systems, specifically in the areas of energy management, demand response, power markets and operational control. Literature [22] proposed a deep reinforcement learning-based cybersecurity assessment method for wind power systems and verified the effectiveness of the method through numerical simulation in a smart power system environment. Although all the above studies have made more satisfactory progress, they still need to be improved.

In this paper, the length of the industrial frequency waveforms collected by the monitoring terminal is firstly selected to determine the relationship between the discharge current and the number of discharges, so as to determine the existence of discharge hazards in the DC cable lines of the distribution network. Then the double-ended traveling wave method is used to locate the fault point precisely, and the entropy value method is used to discretize the fault data. Finally, the causal attribute discrimination between power equipment faults and behaviors is made through reinforcement learning theory, and the key factors leading to the occurrence of power equipment faults are identified, and the evolution path of power equipment faults is further projected. A distribution network is selected as the experimental object, and the cable hidden danger warning effect of the model designed in this paper is evaluated through simulation experiments, and the model is put into practice to further test the practicability of the method proposed in this paper.

2 Reinforcement learning-based optimization of hidden danger warning and fault location in distribution network cables

2.1 Principles of Hidden Danger Early Warning and Fault Localization

2.1.1 Principles of Hazard Warning

Due to the distribution network DC cable lines, cable lines are subject to high humidity, high salinity, and other factors, the cable lines are prone to partial discharges and then derived from irreversible faults, so the DC cable line condition monitoring is extremely important, the system through the monitoring terminal data acquisition data analysis, so as to realize the DC cable line phased early warning, the following is a hidden discharge warning process and algorithms:

Firstly, the duration of the power frequency waveform collected by the monitoring terminal was selected, t_i was the start time of the power frequency, t_j was the end time of the power frequency, Q_0 was the reference value of the hidden discharge, the unit was cc, I_i was the minimum current value of the hidden discharge, I_j was the maximum current value of the hidden discharge, n_1 was the number of discharges in the interval, and n_2 was the number of discharges in the intervalIn order to be greater than the maximum discharge current amplitude I_j, if the discharge current and the discharge number meet the following relationship, it can be determined that there is abnormal discharge in the DC cable line of the distribution network [23].

(1) Take any two numbers from 1 to n Q values, denoted as Q_i and Q_j, if the value of Q is significantly different from the value of I_j and satisfies the relationship between equation (1), it can be judged that there is a hidden discharge situation in the collector line:

$$\begin{gathered} |Qi - Qj| = c \\ Q \geq 1.5Ij \end{gathered} \tag{1}$$

where the c values range from $0 \leq c \leq 0.1\max(Q_i, Q_j)$.

(2) Take two numbers for each of the 1 to l and m to n values of Q.

Denoted as Q_i and Q_j, $1 \leq l < m \leq n$, if there exists more than one consecutive Q_i and Q_j to satisfy the relationship of Equation (2), it can be judged that there is a hidden danger in the cable:

$$Q_i - Q_j = d \tag{2}$$

In the formula, the range of d value is: $d \geq 0.5Q_i$.

Distribution network DC cable meets the above two different discharge conditions are judged as the existence of hidden danger discharge, for the different discharge conditions for the stage of early warning.

2.1.2 Principle of precise fault localization

Because DC cable lines are different from AC lines, it is difficult to identify the reflected wave of the fault point during fault ranging, so the double-ended traveling wave method is generally used for fault location, i.e., the D traveling wave method of fault ranging, and Fig. 1 shows the schematic diagram of the application of the D traveling wave method of fault ranging in DC cable lines of the power distribution network [24].

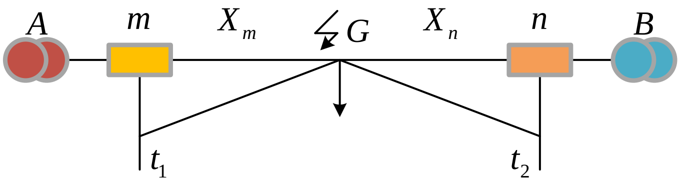


Figure 1: D Schematic diagram of fault location using traveling wave method

A and B are two cable terminations, m,n m,n are traveling wave monitoring terminals, X_m, X_n are the distances between the fault point and the monitoring terminal m and n respectively, point G is the hidden discharge point/fault grounding point of the cable line, t_1, t_2 are the traveling waves transmitted along the transmission line to both ends generated by the fault point G, and equation (3) is the fault ranging formula of the traveling wave method:

$$\begin{cases} \Delta t = |t_1 - t_2| \\ X_m = \dfrac{(L + v * \Delta t)}{2} \\ X_n = \dfrac{(L - v * \Delta t)}{2} \end{cases} \tag{3}$$

2.2 Early warning modeling of distribution cable hazards

Distribution network cable lines are all developmental faults except for force damage faults, and there must be abnormal discharge signals from the early stage of discharge to fault tripping in developmental faults. This system through the monitoring of the very early distribution network cable hidden trouble discharge signal, using the discharge development law to identify, you can realize the cable hidden trouble early warning.

2.2.1 System components

The distribution network cable line is roughly constituted into front-end collection terminal and back-end server, back-end identification algorithm, the field device is responsible for on-site data collection, simple analysis, and then send the data through GPRS form. After selecting the cables to be monitored, the monitoring terminals are respectively installed at the distribution network cable terminal head, Figure 2 shows a schematic diagram of the field monitoring terminal installation location.

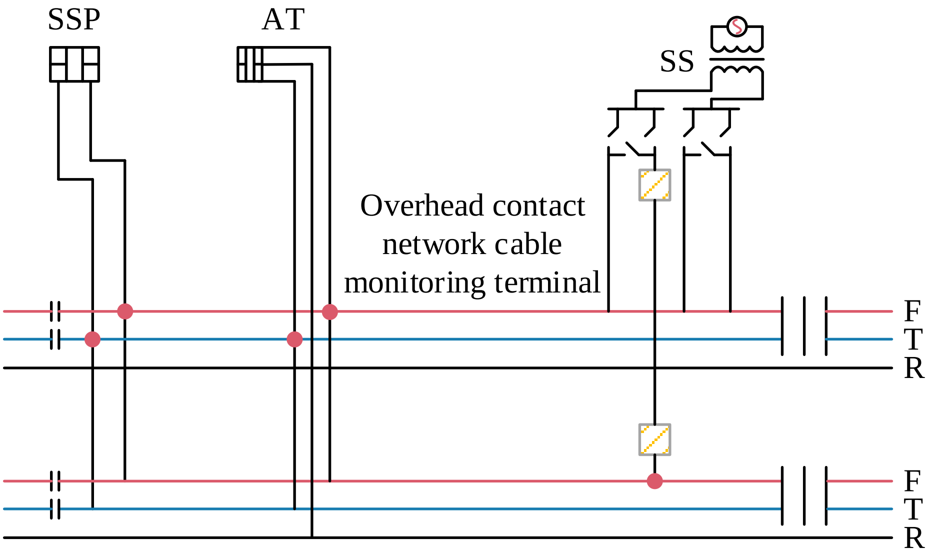


Figure 2: Schematic diagram of monitoring terminal installation

Since the length of distribution network cable lines is generally less than 1 km, the cables are operated with protective grounding at one end, direct grounding at one end, or direct grounding at both ends. In this system, monitoring terminals are installed near the cable terminals at both ends for better condition monitoring of distribution network cables. The monitoring terminal has several sensors, including a current transformer mounted on the core, a temperature sensor mounted near the cable termination, a loop current sensor mounted on the grounding wire, and an IF voltage sensor mounted on the cable skin.

2.2.2 System algorithms

Due to the distribution network cable line faults in addition to external damage faults for transient, other types of faults have a rule to follow. Therefore, the use of monitoring terminals to collect data from the scene, the use of system algorithms for the identification of very early hidden trouble discharges, hidden trouble discharges on distribution network cable lines for early warning, can assist the field operation and maintenance personnel to realize early hidden trouble detection, thus reducing the possibility of the cable line from the hidden trouble discharges evolved into fault tripping.

(1) due to the cable line very early hidden trouble discharge is always in the voltage peak show obvious discharge characteristics, its hidden trouble discharge current intensive point is always in the frequency voltage direct sinusoidal of the great value or the very small value, so the frequency voltage sinusoidal amplitude is greater than 0.8 times the peak as a moment of the discharge interval, that is:

$$U \geq 80\% \times |U_{\max}| \tag{4}$$

The voltage value U above 0.8 times is selected as the characteristic interval of hidden discharge, and the moment solving of the characteristic waveform of hidden discharge is carried out in this interval.

For the obtained t, the set of moments t is solved, then $t = \{t_1, t_2, t_3, t_4, \cdots, t_n\}$, and two adjacent moments are selected for the analysis of the traveling wave current data of hidden discharge uploaded from the monitoring terminal:

$$t = \arcsin(0.8U_{\max}) \tag{5}$$

(2) As the industrial frequency voltage is milliseconds, and the traveling wave voltage is microseconds, it is necessary to select the milliseconds subordinate to the microseconds traveling wave in the adjacent time period in the above step 1 for the very early hidden danger determination. According to the hidden trouble discharge characteristics, the hidden trouble discharge current discharge amplitude of the cable line in the very early stage is mA level, and its discharge always shows extremely similar regularity, so the hidden trouble discharge waveforms in the adjacent time period are selected to obtain the Pearson correlation coefficient of the waveforms.

Intercepting the waveform data with weak discharge current, the Pearson's correlation coefficient is solved for the discharge waveforms in the neighboring discharge time period:

$$p = \frac{\sum_{n=1}^{N} |i_{k1}(n)||i_{k2}(n)|}{\sqrt{\sum_{n=1}^{N} i_{k1}^2(n) \sum_{n=1}^{N} i_{k2}^2(n)}} \tag{6}$$

where, p value is the value of correlation coefficient, if the p value is close to 1, it proves that there is a very strong hidden discharge, if the p value is close to -1, then the system does not exist hidden discharge, i_{k1}, i_{k2} is the waveform data of the neighboring time segments, N is the total length of the waveforms in the presence of weak discharges, and n is the first aberration in the intercepted waveform segments. The number of points, in turn, is calculated for adjacent time segments, and if more than half of the p values are greater than 0.8, the double-ended localization of the traveling wave is performed.

(3) Assuming that half of the p values obtained by the method of step 2 above are greater than 0.8, the precise positioning of the two monitoring terminals is carried out, and the precise positioning is carried out by using the hidden discharge traveling wave within the same milliseconds, and a plurality of precise positioning results can be output, and the positioning statistics are carried out for the output precise positioning results to output the positioning situation.

Solve the hidden trouble discharge waveform fault point location, take the positioning result as the horizontal axis, take the effective positioning times as the vertical axis, can derive the distribution of positioning results, can roughly determine the hidden trouble discharge point of the Internet cable is located in L, so as to realize the hidden trouble point investigation.

(4) The above hidden danger monitoring system is a double-end positioning system, mainly monitoring the hidden danger discharge situation in the section of the Internet cable. According to the principle of double-end traveling wave positioning, the cable terminal near the booster station side can be roughly determined to be located in the position of the hidden danger discharge point between the monitoring terminal and the booster station if the double-end positioning and monitoring device often monitors the hidden danger discharge traveling wave positioning direction in the direction of the reverse direction of the hauling house without carrying out the action of the circuit breaker of the booster station. The location of the hidden discharge point can be roughly determined to be between the monitoring terminal and the traction place. Since the other end of the Internet cable is connected to the contact network line through the cable terminal, it is impossible to determine the hidden

discharge point through the direction of traveling wave source, which may be caused by the train pulling arc, and therefore it is not possible to determine it intuitively. However, through the monitoring device ring current sensor can roughly determine whether there is a hidden problem discharge at the terminal of the cable, and only need to inspect the terminal of the cable manually at regular intervals to realize the hidden problem investigation.

2.3 Reinforcement learning based fault localization optimization

Aiming at the problem of complex fault situations in the field operation of electric power equipment, scholars at home and abroad have proposed a fault localization method based on reinforcement learning: the fault localization algorithm based on reinforcement learning adopts a task-driven learning method, which first classifies and tests the task, and judges the current state of the task through the training results, and reinforces the subsequent tasks. In order to solve the problems of traditional reinforcement-based learning such as the difficulty of discovering problems and the complexity of the learning process.

In this paper, based on traveling wave fault ranging, reinforcement learning is used to achieve further optimization of fault location. The specific methods are as follows: a classifier is used to realize fault localization, and its specific fault location and severity are determined by establishing examples and autoregressive models. The combination of fault probability assignment and fault prediction is realized through adaptive control to predict whether the fault location needs to be evaluated, determined and labeled in the next step. The autoregressive model includes two parts: regression state prediction and regression time prediction. Based on the reinforcement learning algorithm, simulation experiments are conducted to verify the effectiveness of the typical cases. In order to adapt the power equipment fault data to the fault location condition structure, the power equipment fault data is discretized as follows: set the discretization standard of power equipment fault data based on the a priori knowledge, discretize the data using the standard, and use the entropy method to discretize the data for which it is difficult to find a unified discretization standard.

2.3.1 Distributed Power Equipment Fault Data Preprocessing for Distribution Networks

Initialize the interval array and entropy value array of the original data as empty, put the original data into the interval array, put the maximum value of the original data into the entropy value array, select and take out the corresponding entropy value of the largest array from the interval array, and express it with Q, and calculate the entropy value of each interval, which is calculated by the formula:

$$e = \sum \log \frac{m_{ij}}{m_i} \tag{7}$$

where: e denotes the entropy value of the i th interval in the interval array, m_{ij} denotes the number of data in the i th interval whose value belongs to the j th class, and m_i denotes the number of data of the power equipment failure in the i th interval in the interval array. After taking out the smallest entropy value, removing its corresponding entropy value in the entropy value array, removing its corresponding interval in the interval array, and adding the interval corresponding to the largest entropy value in the interval array, and adding its corresponding entropy value in the entropy value array, the discretization of power equipment fault data is carried out in accordance with the above process, which provides the basis for the subsequent fault localization based on reinforcement learning.

2.3.2 Reinforcement learning based fault localization

After determining the existence of power equipment faults, reinforcement learning theory is used to localize the causal attributes between power equipment faults and behaviors, identify the key factors that lead to the occurrence of power equipment faults, determine the subordinate events that may evolve, and predict the direction of the evolution of power equipment faults. Reinforcement learning consists of four elements: intelligence, environment, reward, and action, and Fig. 3 shows the structure of power equipment fault localization based on reinforcement learning.

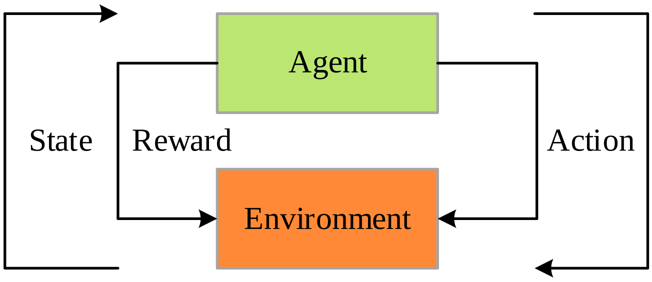


Figure 3: Fault positioning of power equipment based on enhanced learning

The objective of power equipment fault localization based on reinforcement learning is defined as a Markov decision-making process, through which the optimal Markov decision-making strategy is obtained, and its decision-making process is actually a mapping process from power equipment fault states to actions, which is expressed by the formula [25]:

$$\varepsilon(a \mid s) = p(A = a \mid S = s) \tag{8}$$

where: $\varepsilon(a \mid s)$ denotes the Markov decision strategy, i.e., the distribution strategy for getting an action given a power equipment fault state, ρ denotes the reward value obtained, A denotes the finite set of actions for the power equipment, a denotes the intelligences deciding on the action, S denotes the finite set of states for the power equipment, and s denotes the power equipment fault state.

Under the Markov decision-making strategy, the initial state point of the power equipment is taken as the starting point of localization, the intelligent body decides an action and gets the corresponding reward value, and after the intelligent body gets the reward, it makes the power equipment enter into the next state from the initial state, which is a possible subordinate event, and from this, we can get the state chain of the power equipment, and sort all the states in the state chain of the power equipment according to the time sequence, the The beginning of the time series is the root cause of the power equipment fault, i.e., the source fault of the power equipment, the state at the end of the time series is the subordinate event of the evolution of the power equipment fault, and the state chain of the power equipment is the path of the fault evolution, so as to understand the reason for the occurrence of the power equipment fault, as well as the process of the occurrence of the fault and the subsequent state, which in turn realizes the fault localization of the power equipment based on reinforcement learning.

3 Research on hidden danger early warning and fault localization in the environment of intelligent power system

3.1 Early Warning Effect of Distribution Cable Hazards

A distribution network cable is selected as an experimental object, the internal structure data and equipment data are obtained, and the data are transferred to MATLAB software for numerical simulation, which mainly focuses on the operational status of the cable. The simulation mainly focuses on the operational status of the cable, and then use the design method in the paper and the current method to warn of hidden problems. In order to enrich the experimental environment, the cable hazards of the distribution network are set into two parts: cable hazards and environmental hazards. In this experiment, the comparison objects are set as 3 parts: the false alarm rate, the accuracy of cable operation state estimation, and the delay of hidden data transmission, and the results of the comprehensive analysis of the 3 indexes are used to determine the use of the design method in the paper and to complete the comparison with the currently used method.

3.1.1 Early warning false alarm rate vs. accuracy

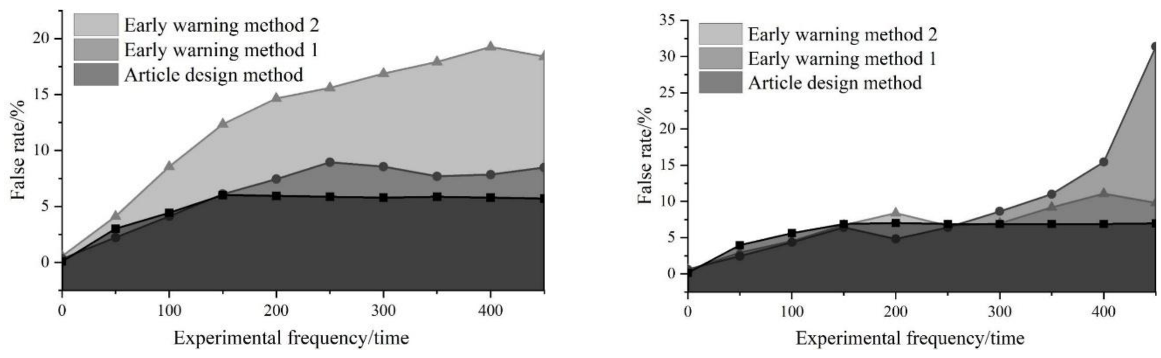
(1) False alarm rate

In the case of cable hazards and environmental hazards, the design method in the paper is compared and analyzed with the early warning method 1 and early warning method 2 for the false alarm rate of cable hazards monitoring and warning, and the comparison results are shown in Fig. 4, with Fig. (a) for cable hazards and Fig. (b) for environmental hazards.

In the experimental setting of the 2 environments, the design method of this paper to get the warning information false alarm rate is significantly lower than the 2 methods currently used. At the same time, by analyzing the 2 test environments, it can be seen that the design method in this paper, whether in the case of cable hazards or environmental hazards, the false alarm rate of its warning is within 8%, which is lower than the currently used methods.

(1) Early warning method 1 has the lowest alarm efficiency among the three methods, and its chance of false alarm is higher.

(2) The alarm effective rate of early warning method 2 is higher than that of early warning method 1, but there is still a certain gap compared to the early warning effective rate of the method designed in the paper. The analysis of the previous cable hazard warning situation shows that the false alarm rate of the warning seriously jeopardizes the service life of the cable. Therefore, the above analysis results determine that the design method in the paper is superior to the two methods currently used.



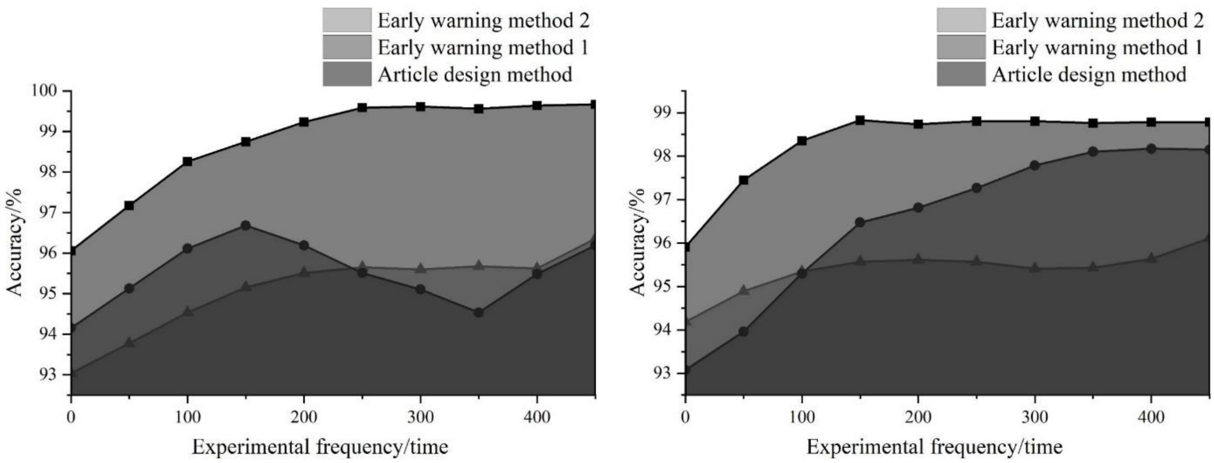
(a)Cable hazard (b)Environmental hazard

Figure 4: Comparison results of early warning false alarm rate

(2) Accuracy

In the two cases of cable hidden danger and environmental hidden danger, the design method in the paper is compared and analyzed with the precision of cable operation state estimation carried out by the early warning method 1 and the early warning method 2, and the comparative results are shown in Fig. 5, with Fig. (a) showing the cable hidden danger and Fig. (b) showing the environmental hidden danger.

According to the above experimental results of cable operation state estimation accuracy, it can be seen that the design method in the paper has a higher precision for the analysis of cable operation state, especially in the case of cable hidden danger, after the number of experiments reaches 250 times, the accuracy of the warning is kept at 99%, infinitely close to 100%, and the advantages of the design method in the paper are clearly demonstrated. Compared with the design method in the paper, the 2 methods currently in use are less capable of analyzing the cable operation state, and the precision of the state estimation obtained in the 2 experimental environments varies greatly. It is clear from the analysis that this state is due to the poor ability of the 2 currently used methods to characterize the use of the cable. Because the method in this paper utilizes the discharge development law identification to construct a cable state warning model, it improves the precision of cable operation state estimation and the monitoring and warning capability of cable equipment, both in the case of cable hidden danger and environmental hidden danger. At the same time, the precision of cable operation state estimation affects the warning effectiveness of the warning method, and a comprehensive analysis of this result with the results of the previous group of experiments shows that the design method of this paper has certain comprehensive advantages.



(a)Cable hazard (b)Environmental hazard

Figure 5: Comparison results of accuracy of cable operation state estimation

3.1.2 Distribution network equipment fault data preprocessing warning signal processing

The key of this paper is to realize the acquisition and processing of the hidden problem situation of power distribution equipment, power distribution network equipment are mostly high voltage and high current switchgear, easy to produce strong interference, in the field of stronger interference conditions, the signal is often drowned in the noise is difficult to deal with, Fig. 6 is the original signal. In this paper, in the intelligent power system environment, using the early warning model proposed in this paper, the distribution network equipment fault data preprocessing, the original signal fluctuates between [-0.4,0.4].

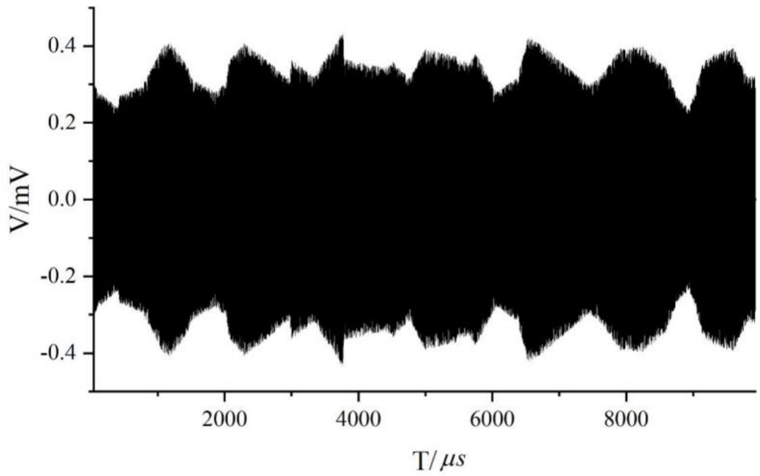


Figure 6: Primary signal

In order to meet the demand for accuracy, the original signal must be denoised, and this paper adopts discretization processing, according to the processing steps of 2.3.1, the signal after three times of discretization processing is shown in Fig. 7. The signal concentrates most of the energy of the original signal, the trend direction is clearer, and the signal range is reduced to between [-0.3,0.3], and its discretization effect is conducive to signal discrimination and analysis.

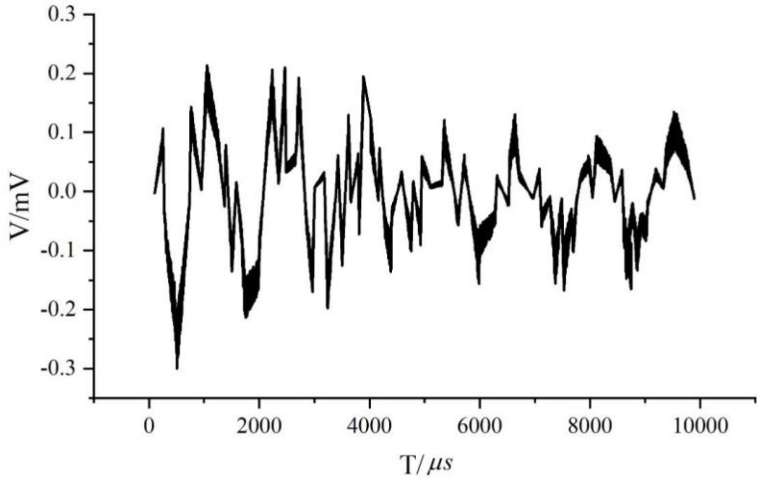


Figure 7: Signal after discretization

3.1.3 Early warning response time

The results of the algorithm response time test are shown in Figure 8.The fastest response time of the BP neural network algorithm is 0.5359s, the slowest response time is 1.1658s, and the average response time is 0.8251s.The fastest response time of the SVM algorithm is 0.5216s, the slowest response time is 0.9169s, and the average response time is 0.6799s.The fastest response time of the PNN algorithm is 0.4536s, and the slowest response time is 0.7715s. response time is 0.4536s, the slowest response time is 0.7715s, and the average response time is 0.5804s.The algorithm in this study outperforms the above three algorithms in terms of the fastest response time, the slowest response time, and the average response time, which are 0.3569s, 0.7259s, and 0.5328s, respectively.

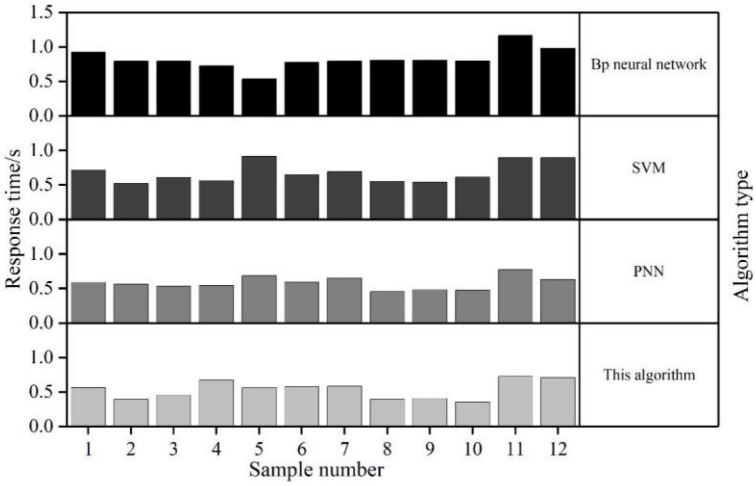


Figure 8: Algorithm response speed test results

3.1.4 Effectiveness of Early Warning Practice for Distribution Network Cable Hazards

In order to further validate the practicability of the method proposed in this paper, and to test whether the method can bring some practical effects to distribution network users, the method was piloted for one year in the users belonging to the target distribution network lines. From the point of view of the consumers, the number of accidents occurring in the consumers is analyzed as shown in Fig. 9.

In the year before the proposed method was put into use, the average number of monthly occurrences of power accidents reached 312, while in the month when it was put into use, the method reduced the number of occurrences of power accidents to 91 because of the timely warning of the cable hazardous lines. And with the extension of the use of time, the superiority is more and more significant, the trend of reducing the number of accidents is gradually linear development, the pilot phase of the average monthly number of accidents in the user's electricity only 61 times. This allows the user's electricity safety has been greatly improved, the probability of accidents and potential hazards significantly reduced, optimizing the user's electricity experience.

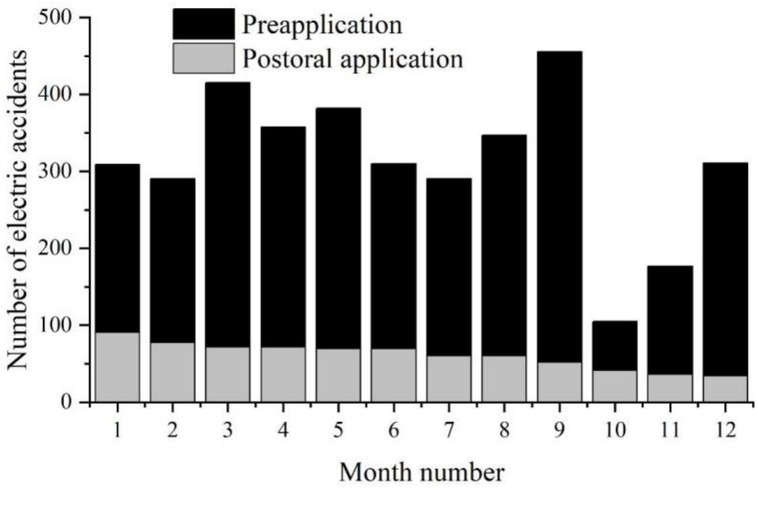


Figure 9: Number of electrical accidents occurred by users

Based on the economic benefits of electric power enterprises, the practical value of the proposed method is verified. The economic benefits of electric power enterprises are shown in

Figure 10.

Before the method was put into use, the average monthly power gain was 148,452,000 yuan, while in the month when the method was put into trial operation, the power gain increased by 153,020,000 yuan compared with the same period of last year, and the amount of the gain continued to rise over time, resulting in a total annual gain of up to 4,476,838,000 yuan in the operation phase, which was a rise of 151.3 percent compared with that before the use of the method. This is because the proposed method accurately warns of the risk of cable hazardous lines and timely eliminates the user's electricity safety hazards, thus indirectly bringing great economic benefits to the enterprise, with obvious advantages and potentials for use in actual operation.

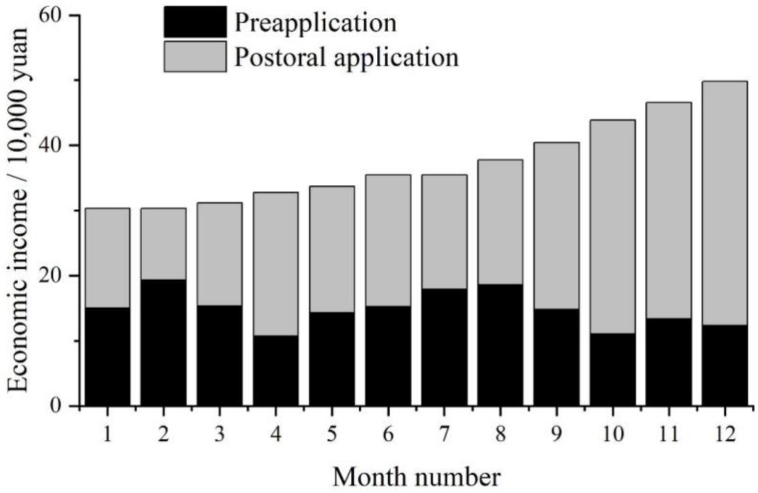


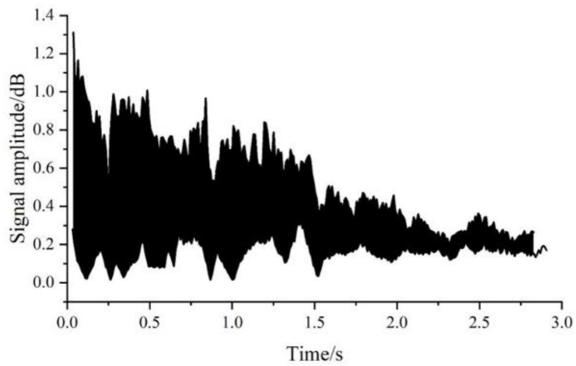
Figure 10: Economic benefits of power enterprises

3.2 Analysis of fault localization results

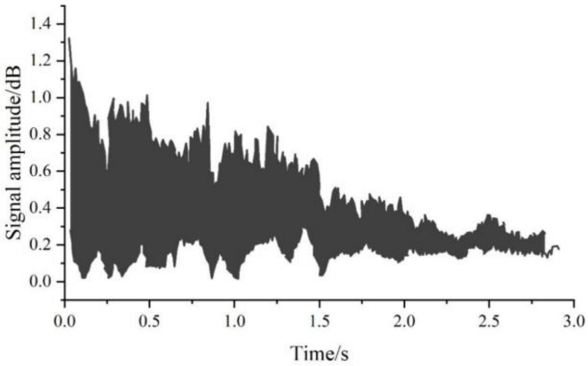
3.2.1 Time domain characterization results

By analyzing the features of traveling wave fault signals in time and frequency domains, the ability of the above recognition methods to locate traveling wave fault signals in noise-containing environments is evaluated, and the results are shown in Fig. 11, where Figs. (a) and (b) are the original signals, Figs. (c) and (d) are the traveling wave fault signals localization based on reinforcement learning, and Figs. (e) and (f) are the fault localization based on SR-VMD.

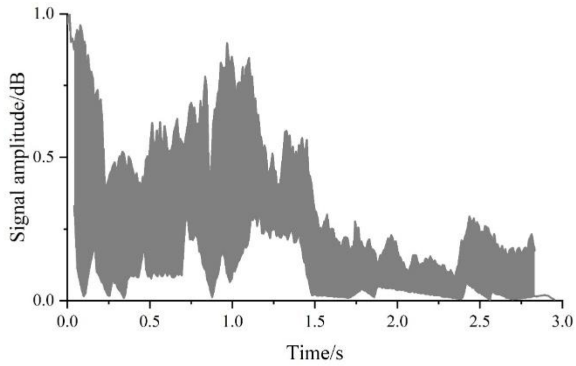
By analyzing the characteristics of traveling wave fault signal in time and frequency domains, it can be seen that under the noise environment, the signal extraction results of the traveling wave fault signal localization based on reinforcement learning can still be closer to the time and frequency characteristics of the original signal, and with the increase of time, the traveling wave signal is gradually weakened, and fluctuates steadily in the range of 0.1~0.3dB after 2.6s. The time-frequency feature extraction results based on SR-VMD, on the other hand, show obvious deviation from the original signal, which verifies the accuracy and reliability of this paper's algorithm in extracting and analyzing the traveling wave fault features.



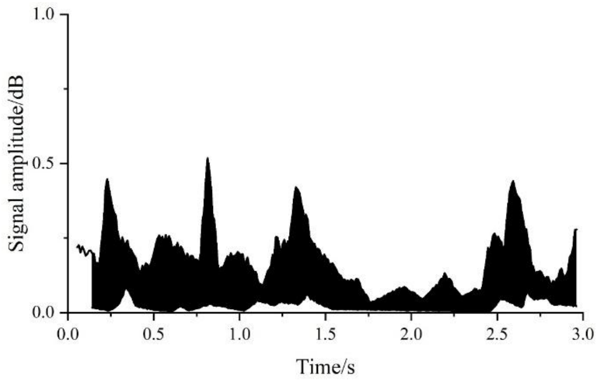
(a)Primary signal



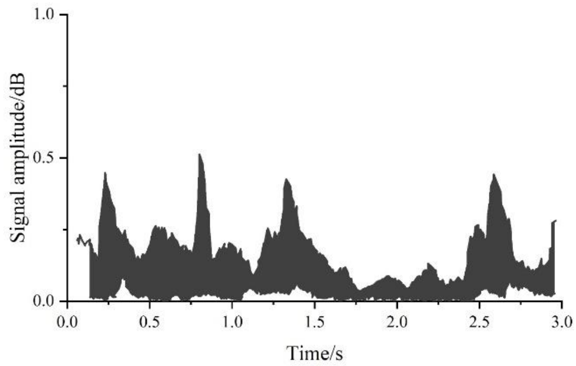
(b)Primary signal



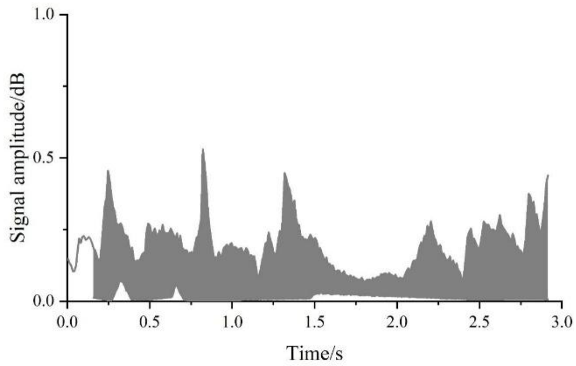
(c)Based on strengthening learning, the fault signal is located



(d)Based on strengthening learning, the fault signal is located



(e)Fault localization based on SR-VMD



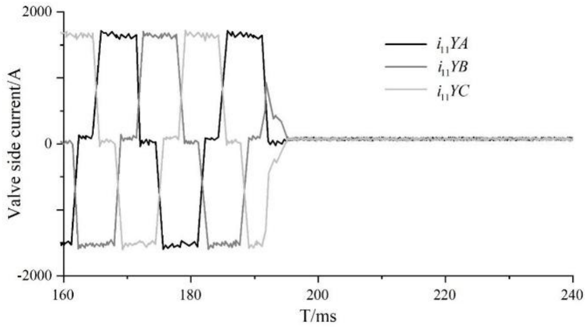
(f)Fault localization based on SR-VMD

Figure 11: Analysis of frequency characteristic analysis

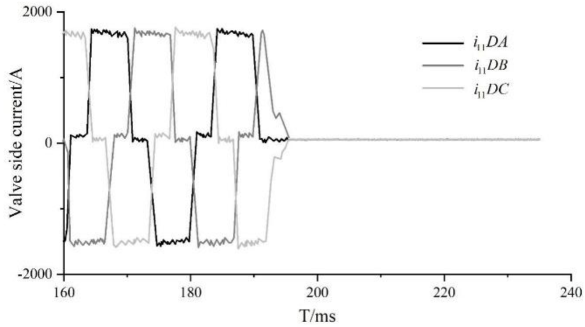
3.2.2 Fault localization and verification

After the fault localization system of reinforcement learning in this paper is located, extracting the main event message of a distribution network cable fault, it can be seen that the pole 1 DC differential protection action can be preliminarily judged that the pole 1 has occurred a grounded short-circuit fault. Pole 1 low valve Y-bridge and D-bridge short-circuit protection are operated, it can be initially judged that the fault point is located in pole 1 low valve. DC control protection fault recording as shown in Figure 12, Figure (a), (b) for pole 1 high valve Y bridge, D bridge, Figure (c), (d) for pole 1 low valve Y bridge and D bridge, Figure (e), (f) for DC current and differential current.

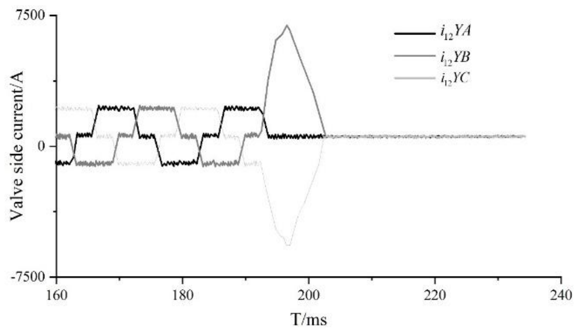
The 5 differential currents were basically stable near 0 at the beginning of the recording (during normal operation), and at about 190-205ms, ΔI_3, ΔI_5 underwent a sudden change in which the amount of change in ΔI_3 was much larger than that in ΔI_5, and a current fluctuation of nearly 7000A occurred. It was initially determined that a ground fault had occurred in the area corresponding to ΔI_3. Combined with the fact that the three-phase currents $i_{11}DA$, $i_{11}DB$, $i_{11}DC$ on the valve side of the Pole 1 High Valve D-bridge decrease rapidly after the fault, a short-circuit fault in the grounding of the Pole 1 High Valve D-bridge can be ruled out. Also due to the pole 1 low valve Y bridge fault when the B phase current is positive, the fault when the B phase upper bridge arm conduction, $i_{12}YB$ abnormally increased, suggesting that it may be the B phase and the high and low valves in the region of the mid-point of the short-circuit grounding occurred. Field test results show that the actual fault is a DC through-wall casing grounded short circuit fault near the measurement point, consistent with the analysis.



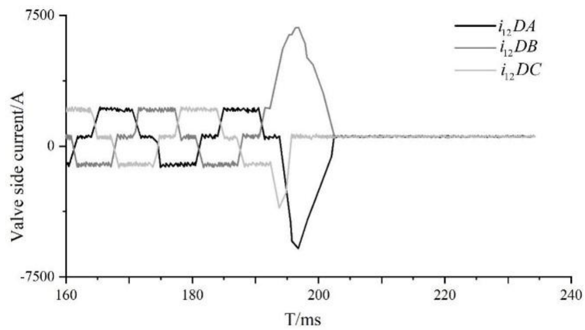
(a)Pole 1 high valve Y bridge



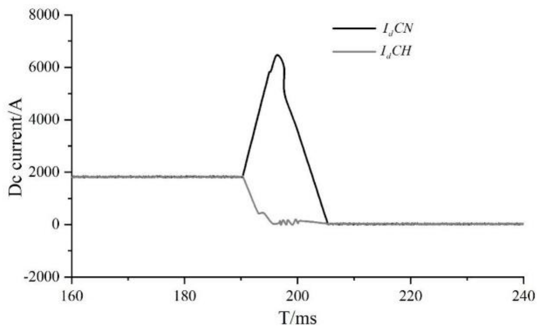
(b)Pole 1 high valve D bridge



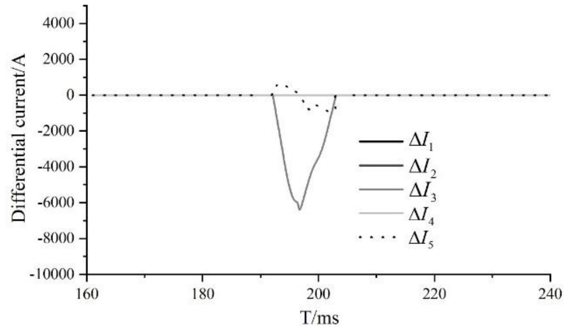
(c)Pole 1 low valve Y bridge



(d)Pole 1 low valve D bridge



(e)Dc current



(f)Differential current

Figure 12: Dc control protection fault recording

4 Conclusion

In this paper, based on the principle of hidden danger early warning and fault localization, a cable hidden danger early warning model for distribution network is constructed by using the method of identifying the discharge development law to realize the cable hidden danger early warning. At the same time, based on traveling wave fault ranging, combined with reinforcement learning, the fault location is further optimized, and the entropy value method is used to discretize the fault data of power equipment.

(1) The cable hidden danger early warning system designed in this paper has a false alarm rate of less than 8% in both cable hidden danger and environmental hidden danger cases, which is better than the two methods in comparison. For the accuracy of the cable operation state in the number of experiments carried out to 250 times after the maintenance of about 99% close to 100%, can be seen in this paper design method has a certain comprehensive advantage.

(2) Detection of the method for the distribution network users to bring the actual role, put into the first month of the early warning system, will reduce the number of customer power accidents to 91 times, the average monthly number of customer power accidents during the trial period of only 61 times. And the total annual revenue of the operation phase is up to 4,476,838,000 dollars, which is 151.3 percentage points higher than before the use.

(3) The fault localization was verified. At about 190-205ms, ΔI_3, ΔI_5 had a sudden change in which ΔI_3 had a current fluctuation of nearly 7000A, and it was initially concluded that ΔI_3 A ground fault occurred in the corresponding area. After the field test, the actual fault is a short-circuit fault of the DC through-wall casing grounding near the measurement point, which is consistent with the analysis.

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