International Journal for Housing Science and Its Applications
Publish August 5, 2025. Volume 46, Issue 3 Pages 4515-4523

https://doi.org/10.70517/ijhsa463387

Research on new distribution system state sensing and early warning technology combined with time series data analysis

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Abstract Under the large amount of distributed energy access, the operation state of the distribution system becomes more and more complex, and the traditional state sensing method is difficult to meet the demand for high precision. This paper aims to realize real-time state sensing and early warning of the new distribution system, calculates the equivalent electrical distance of nodes, and adopts the voltage-active power sensitivity to characterize the electrical distance between nodes, so as to closely connect the nodes in the region. On this basis, a Bayesian network is introduced to design a time series simulation method for distribution network components and system state respectively, so as to perceive the distribution network system state in real time. Integrating multiple sources of distribution information, including grid monitoring, user feedback and environmental detection, and constructing a fault indicator fusion information matrix, real-time monitoring and fault warning of the distribution network system state are realized. In the practical application of this method, the abnormal situation can be sensed in 2s and the warning response can be activated in 3s, which has high warning speed and response sensitivity.

Index Terms Bayesian network, real-time monitoring, fault warning, distribution network system

I. Introduction

In recent years, the penetration rate of distributed energy in all levels of the power system has been increasing, and its intermittent and uncertainty characteristics make the power system, especially the safe and stable operation of the distribution system, face serious challenges [1]-[3]. For this reason, countries around the world have accelerated the reform of energy structure, resulting in significant changes in the structure of the electric power industry, and a new type of distribution system with a high proportion of new energy features has emerged [4]-[6].

The construction of a new type of distribution system is an inevitable requirement for building a new type of energy system and a new type of power system, which will provide a solid guarantee for energy transformation and sustainable socio-economic development through continuous efforts to realize its goals of safety and efficiency, cleanness and low carbon, flexibility and flexibility, and wisdom and integration, and to promote the transformation of the distribution network's form and function [7]-[10]. However, this requires the joint efforts of the government, enterprises, research institutions and other parties to strengthen cooperation and innovation, and jointly move towards a cleaner, smarter and more reliable energy future [11]-[13]. The new distribution system as the key to the power system, integrated distributed energy facing challenges such as diverse loads and changing demand, leading to complex failure scenarios and risk enhancement, requiring higher security and stable operation [14]-[16]. The new distribution system requires the realization of refined operation management and accurate perception of real-time state, while state perception and early warning is an effective means to ensure system security, the traditional disposal methods are slow to respond, inaccurate positioning and long recovery, which is difficult to meet the needs of the new system [17]-[20].

This paper firstly describes the methodology and steps for computing the voltage-active power sensitivity equivalent to the electrical distance between nodes in the distribution network system. The Bayesian network algorithm is chosen as the time series simulation method of the distribution system under the setting of nodes in the closely connected distribution network area. The time series simulation process of component and system states in the distribution system is discussed in detail to realize the real-time perception of the distribution system state. Then, we explain the state representation of multiple parameters in the distribution system and design a fault warning method for the distribution system that integrates multi-source information. Finally, the effectiveness of the proposed distribution system state sensing and fault warning methods are tested by comparing similar methods.

II. Bayesian Networks Based Sensing and Early Warning for Power Distribution Systems

II. A. Node equivalent electrical distance

When partitioning the distribution network, it is necessary to consider dividing the nodes with strong electrical connections into the same subregion as much as possible, so that the nodes in the region maintain strong connections. When using the traditional Newton-Raphson method to calculate the system current, the linearized polar form of the current equation is given in equation (1):

$$\begin{bmatrix} \Delta P \\ \Delta Q \end{bmatrix} = J \begin{bmatrix} \Delta \delta \\ \dfrac{\Delta U}{U} \end{bmatrix} \tag{1}$$

where: ΔP and ΔQ are the variations of active and reactive power injected at each node, respectively. $\Delta \delta$ and $\Delta U / U$ are the variations of phase angle and amplitude of the node voltage, respectively. J is the Jacobi matrix of the current equation as in equation (2):

$$J = \begin{bmatrix} \dfrac{\partial P}{\partial \delta} & \dfrac{\partial P}{\partial U} U \\ \dfrac{\partial Q}{\partial \delta} & \dfrac{\partial Q}{\partial U} U \end{bmatrix} = \begin{bmatrix} H & N \\ J & L \end{bmatrix} \tag{2}$$

where: P, Q, U, δ are the node injected active power, reactive power, voltage magnitude and phase angle respectively. H, N, J, L are intermediate variables.

Eq. (3) is obtained from Eqs. (1) and (2):

$$\Delta P = HJ^{-1}\Delta Q + \left(N - HJ^{-1}L\right)\frac{\Delta U}{U} \tag{3}$$

In the distribution system, the ratio of the voltage variation of node i to the active power variation of node j is approximated as the voltage-active power sensitivity of nodes i and j, and the electrical distance between the nodes is characterized by the sensitivity, and the formula for each element of the sensitivity matrix can be written as equation (4):

$$S_{ij} = S_{ji}^{-1} = (\Delta U_i / U_i) / \Delta P_j \tag{4}$$

where: S_{ij} is the voltage-active power sensitivity, which indicates the change in active power at other nodes caused by an increase in voltage at one node. U_i and ΔU_i are the voltage magnitude of node i and its variation, respectively. ΔP_j is the change in power at node j. The electrical distance between nodes i and j after symmetrical treatment of electrical distance can be written as equation (5):

$$k_{ij} = k_{ji} = \sqrt{S_{ij}^2 + S_{ji}^2} \tag{5}$$

II. B. Bayesian network timing simulation process

II. B. 1) Component state timing simulation

In this paper, the two states of the component are illustrated as an example, and only the normal and faulty (repair) states of the component are considered, so that the component operates in a time-series simulation process that spans alternating transitions between the normal and faulty states over a long simulation time is shown in Fig. 1. A "low" level indicates a normal state, a "high" level indicates a faulty state, and T_{ik} represents the time at which i is generated for the k th time.

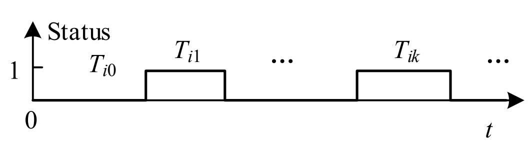


Figure 1: Simulation of sequential elements

In analyzing the reliability of a system, it is generally assumed that the failure and repair rates of components are constants, and that the life and repair time of components follow an exponential distribution.

The probability density function of the normal state can be expressed as: $f_0(t)=e^{-\lambda t}$, and taking the natural logarithm yields: $\ln f_0(t)=-\lambda t$, which gives us equation (6):

$$t=-\frac{1}{\lambda}\ln f_0(t)=-T_{MTTF}\ln f_0(t) \tag{6}$$

where $f_0(t)$ - a value taken in the middle of 0 to 1, λ - probability at failure, T_{MTTF} - the mean trouble-free operating time of the component, also known as the mathematical expectation of the operating life, t - the time at this reliability rate.

The probability density function of the failure state can be expressed as $f_1(t)=e^{-\mu t}$, and taking the natural logarithm gives $\ln f_1(t)=-\mu t$, which gives equation (7):

$$t=-\frac{1}{\mu}\ln f_1(t)=-T_{MTTR}\ln f_1(t) \tag{7}$$

where $f_1(t)$ - a value taken in the middle of 0 to 1, μ - probability at normal time, T_{MTTR} - average repair time of the component, t - the time at that probability of failure.

Combining the above two equations yields the duration of the i th element in the k th transition state as in equation (8):

$$T_{ik}=\begin{cases}-T_{MTTF}\ln r & \textit{When the component is normal}\\ -T_{MTTR}\ln r & \textit{When the component fails}\end{cases} \tag{8}$$

Replacing r in Eqs. (7)-(8) with $f_0(t)$ and $f_1(t)$ in Eqs. (7)-(8) represents the probability of being faulty or the probability of being normal, and is generated as a random variable in the range $(0,1)$. When the component is normal, the duration of the normal state is calculated according to $T_{ik}=-T_{\mathrm{MTTF}}\ln r$. When the component is faulty, the duration of the faulty state is calculated according to $T_{ik}=-T_{MTTR}\ln r$.

In this paper, the random variable r is generated in the range of $(0,1)$ according to the congruence method, and the specific steps are shown in Eqs. (9)-(10):

$$Z_i=(aZ_{i-1}+c)\bmod M \tag{9}$$

$$r_i=Z_i/M \tag{10}$$

where i - the number of random numbers generated, a - constant, equal to 16807, Z - the seed.

c - constant, equal to 0, M - equal to $2^{31}-1=2147483647$, "mod" - apply the rest of the numbers.

With the above values, full-cycle sampling can be achieved, producing pseudo-random numbers that do not repeat each other. When $i=1$, $Z_{i-1}=Z_0$, called the initial seed.

Let an initial seed be some positive integer, and then substitute it into Eq. (9) to get the seed Z_1, and then substitute it into Eq. (10) to get the first random number r_1, and then substitute Z_1 into the right hand side of Eq. (9) to get Z_2, and substitute it into Eq. (10) to get the second random number r_2, and so on to get the i th random number r_i.

Substituting the generated random number r into Eq. (8), the state and duration of the component can be obtained, and the simulation steps for the state timing diagram of the component are as follows:

(1) Determination of initial state and duration of components. There are n components, the initial state of each component are set to "normal" state. Using the linear congruence method to generate the random number r in Eq. (7), and substituting it into the above equation of (9), the initial simulation time of the corresponding component i is T_{i0}, and the smallest initial simulation time of n components is taken, i.e., $T_0=\min\{T_{i0}\}$, which is said to be the smallest duration time of T_0.

(2) Determination of the $k+1$th state and duration of the element. Assuming that the kth simulation time of the ith element is T_{ik} and the minimum duration is $T_k = \min\{T_{ik}\}$, the $k+1$th state and duration simulation time of the ith element is equation (11):

$$T_{i,k+1} = \begin{cases} T_{ik} - T_k & \begin{array}{l} T_{ik} \neq T_k \text{When} \\ \text{Holding state} \end{array} \\ \begin{array}{l} \text{Sampling } T_{i,k+1} \\ \text{according to equation (3-3)} \end{array} & \begin{array}{l} T_{ik} = T_k \text{When} \\ \text{Change state} \end{array} \end{cases} \left(i = 1, 2, \cdots, n\right) \tag{11}$$

II. B. 2) System state timing simulation

The state of each component in the minimum time period T_k can only be one case, i.e., normal state or fault state. The timing diagram of the load node is derived from the "or" logical relationship between the component node and the load node, and thus the timing diagram of the load node can be derived from the timing diagram of the system node based on the "cause and effect" relationship between the system node and the load node. Figure 2 depicts the timing diagrams of two load nodes A and B and the timing of system node C.

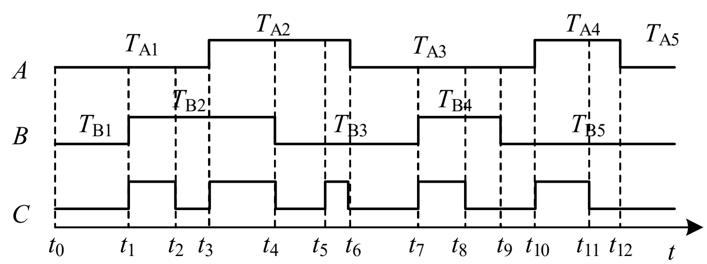


Figure 2: Time sequence simulation for causal relations

In the timing simulation of Fig. 2, the "high" or "low" of the system node C at each minimum duration is determined causally:

(1) When both A and B are "low", the system C is "low", indicating that the system is energized at this minimum duration. For example, $t_0 t_1$ and $t_6 t_7$ time periods.

(2) When both A and B are "high", the system C is "high", indicating that the system is in a blackout state for this minimum duration. For example, time period $t_3 t_4$.

(3) When A is "high" and B is "low", the probability of the system node C to be energized is $n_B/(n_A+n_B)$, the time to be energized is $T_k \times \dfrac{n_B}{n_A+n_B}$, and the power loss time is $T_k - T_k \times \dfrac{n_B}{n_A+n_B}$, indicating that the system is out of power for $T_k - T_k \times \dfrac{n_B}{n_A+n_B}$ during this minimum duration. As in the time period $T_k = t_4 t_6$, the time period $t_4 t_5$ is the power gain time of the system node C and $t_5 t_6$ is the power loss time of the system node C.

(4) When A is "low" and B is "high", the system node C is energized for $T_k \times \dfrac{n_A}{n_A+n_B}$ and de-energized for $T_k - T_k \times \dfrac{n_A}{n_A+n_B}$. For example, $t_2 t_3$ and $t_8 t_9$ time periods are the power gain times of system node C, and $t_1 t_2$ and $t_7 t_8$ are the power loss times of system node C.

Similarly, if the system contains m load nodes, and the number of users in each load node is n_1, $n_2 \cdots\cdots n_m$, and assuming that in a minimum duration, the first l load nodes get power and the rest of the load nodes lose power, the probability of getting power in this minimum duration is $\frac{\sum_{i=1}^{l} n_i}{\sum_{i=1}^{m} n_i}$, the power gain time is $T_k \times \frac{\sum_{i=1}^{l} n_i}{\sum_{i=1}^{m} n_i}$, the power loss time is $T_k - T_k \times \frac{\sum_{i=1}^{l} n_i}{sum_{i=1}^{m} n_i}$.

II. C.Multi-information fusion method for fault warning and diagnosis

In the practical application of fault diagnosis in distribution networks, under the influence of various factors such as the installation location of the fault indicator, the quality of data acquisition, and environmental factors, there are certain errors or inaccuracies in the current, electric field, and flopping information it collects. In order to effectively solve the problem, this paper adopts the method of multi-information fusion to synthesize the collected information. To this end, this paper constructs a matrix called "fault indicator fusion information array" (CTIL) as in Eqs. (12)-(13). This matrix comprehensively records the integrated information of current, electric field, and flip-flop collected by the fault indicator. The matrix utilizes the fusion of information from multiple data sources, which not only enriches the diagnostic basis, but also enables the use of specific algorithms to optimize and correct the information, which effectively reduces the errors and uncertainties that may be associated with a single data source. The application of this method significantly improves the accuracy and reliability of the data, laying a more solid foundation for fault diagnosis. At the same time, the construction of the fault indicator fusion information array also provides great convenience for subsequent data analysis and fault localization, making fault diagnosis more efficient and accurate. In summary, the use of the multi-information fusion method and the construction of the fault indicator fusion information matrix (CTIL) provide a powerful technical support for the accuracy and reliability of fault diagnosis in distribution networks, and further enhance the stability and security of the power system. With this approach, the information provided by fault indicators can be more effectively utilized to provide more accurate data support for fault detection and diagnosis in distribution networks.

$$CTIL = \begin{bmatrix} CL_{11} & CL_{12} & \cdots & CL_{1j} & \cdots & CL_{1m} \\ CL_{21} & CL_{22} & \cdots & CL_{2j} & \cdots & CL_{2m} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ CL_{n1} & CL_{n2} & \cdots & CL_{nj} & \cdots & CL_{nm} \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots \\ CL_{m1} & CL_{m2} & \cdots & CL_{mj} & \cdots & CL_{mm} \end{bmatrix} \tag{12}$$

$$CL_{ij} = \begin{cases} AL_{ij} + EL_{ij} + FL_{ij} - 1 \\ AL_{ij} \neq 1, EL_{ij} \neq 1, FL_{ij} \neq 1 \\ AL_{ij} = -1, EL_{ij} = -1, FL_{ij} = -1 \end{cases} \tag{13}$$

In a simple distribution network, the fault indicator fusion information array $(CTIL)$ shown in Eq. (12) and Eq. (13) is used to comprehensively record the integrated fault information captured by the fault indicators on each feeder. Each row represents a feeder, the number of rows n corresponds to the total number of feeders in the distribution network, and the number of columns m indicates the number of indicators on the feeder with the highest number of fault indicators.

In this matrix, CL_{ij} is a key element that represents the fusion value of fault information collected by the j th fault indicator on the i th feeder. If a fault indicator does not exist, then the corresponding CL_{ij} value is -1. Using the $CTIL$ matrix, it is possible to proactively investigate faults and determine the specific intervals in which faults occur. Look at each row of the $CTIL$ matrix, especially the first row. In the distribution network fault diagnosis model, if a row of data consists of all 0 or -1, then it means that the feeder is not faulted and is in normal operation. When 1 or 2 appears in the row of data, it indicates that there may be a fault, which needs to be further analyzed and diagnosed. If a row of data includes both 1 and 2, it usually indicates a more complex fault scenario. In order to pinpoint the fault point, the system takes these elements, which represent fault indicators, and sorts them according to the order of current flow. This step is crucial as it helps to identify the exact location where the fault occurs, i.e., in the area downstream of the last indicator marked as faulty. With this method, not only can the point of fault be diagnosed quickly, but also the efficiency and accuracy of fault handling can be significantly improved, reducing the duration and scope of outages caused by faults. In addition, the strategy helps optimize maintenance schedules, analyze historical fault data, and predict potential problem areas so that measures can be taken in advance to further enhance the reliability and resilience of the distribution network. In summary, this fault diagnosis method based on data analysis and current flow sequencing provides a strong technical guarantee for the safe and stable operation of distribution networks.

Finally, each row of the fault indicator fusion information array $CTIL$ is continuously analyzed until all rows have been examined, which ensures that the fault condition of each feeder is investigated and the fault interval is accurately determined. By adopting this method, the fault conditions in the distribution network can be comprehensively and systematically grasped, providing strong support for the subsequent maintenance work.

III. Examination and Application of Distribution System Sensing and Early Warning Methods

The main contents of this chapter are the proposed distribution system sensing method, the comparison with the sensing effect of similar methods, the sensing performance under different distribution network operation states, and the practical application test of the proposed distribution system warning method.

III. A. Examination of distribution system sensing methods

III. A. 1) Comparison of perceptual results

The anomalous data occurring during the operation of the distribution network system is used as the experimental control group, which fluctuates in the range of 40 to 50 values, and the traditional neural network-based method (Method2), the method based on the long and short-term memory network (Method3), and the method of this paper are used to make a numerical comparison as a means of verifying the reliability of the method of this paper, respectively. The number of experiments is 80, and the comparison of anomalous data perception results of different methods is shown in Fig. 3.

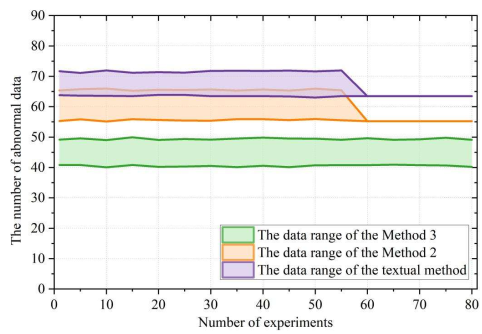


Figure 3: Comparison of abnormal data perception results by different methods

As can be seen in Figure 3, the number of abnormal data can be perceived quickly using the method of this paper, and the perception is stable at 40~50, which is consistent with the control group. While using the method based on neural network (Method2) and the method based on long and short-term memory network (Method3) method to perceive the abnormal data remains at 60~70 and 55~65 respectively, which is a great deviation from the actual situation. The experimental results prove that the use of the methods in this paper can effectively perceive abnormal data, which helps to realize the correction and processing of the data, and truly reflects the operation status of the power distribution system.

III. A. 2) Perceived effects of different operating states

Using the distribution system operation state sensing method based on multi-source data fusion, we analyze the sensing results under different operation states.

(1) Zero sequence voltage.

The ungrounded zero sequence voltage jumps are used to identify the zero sequence voltage at the injection point and to discover the security problems in the distribution system, and the resulting zero sequence voltage security posture is shown in Fig. 4. At 0~2s and 8~10s, the value of the node voltage is 0, and at this time, the distribution system is in a normal operating state. At 2~8s, the node has a certain phase ground fault, at this time, the distribution system does not take into account the load fluctuation, the zero sequence voltage value appears to fluctuate with a large amplitude.

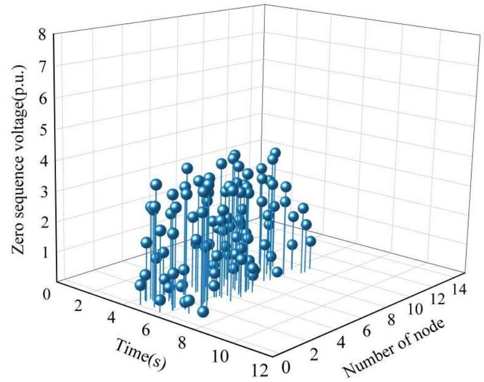


Figure 4: Zero-sequence voltage safety situation

(2) Overrun voltage.

Collect the safety posture information of the injection point, analyze the risk of voltage overrun at each node of the system, and the full posture of overrun voltage obtained without considering the distribution load fluctuation is shown in Fig. 5. At 0~2s, the voltage overrun margin value of each node is 0.91, and at this time, the distribution system is in the normal operation state. In 2~12s, the voltage overrun margin value rises from 0.91 to 1.00, indicating that there is a risk of voltage overrun in the distribution system, and large voltage fluctuations will lead to the distribution system can not work normally, and there may also be burned out appliances.

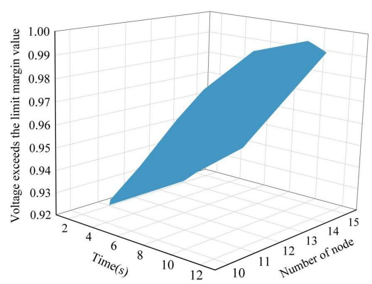
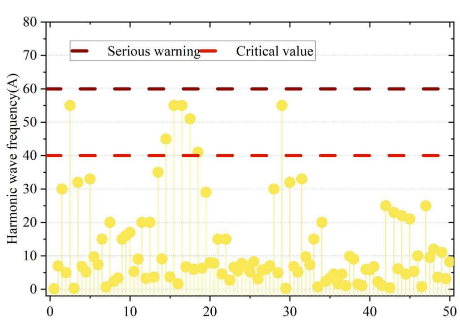


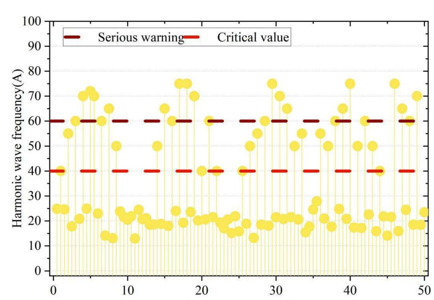
Figure 5: Over-limit voltage safety situation

III. B. Practical application of early warning for distribution network operation

In order to guarantee the early warning effect of the method in this paper, the change characteristics of the harmonic spectrum of the distribution system are shown in Fig. 6, Fig. 6(a) is the harmonic spectrum of the distribution system under the regular operation environment, and Fig. 6(b) is the harmonic spectrum of the distribution system under the operation environment of the abnormal data.



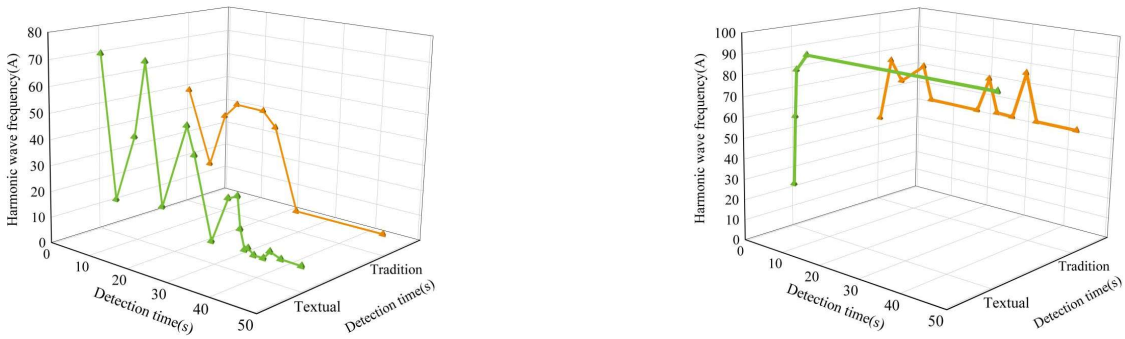
(a) Conventional environment



(b) Abnormal data

Figure 6: Distribution network operation wave frequency sample

Comparative detection is carried out based on the above wave frequency features to analyze the early warning response of this paper's method and the traditional neural network method under the same environment, and the specific detection results are shown in Fig. 7.



(a) Conventional environment (b) Abnormal data

Figure 7: Comparison detection results of fault early warning response situations

Based on the comprehensive analysis of the comparison detection results in Figure 7, it is not difficult to find that, relative to the traditional method, the multi-information fusion of distribution system warning method proposed in this paper in the process of practical application, the warning response sensitivity is higher, in the case of abnormal data in 2s has been detected anomalies and early warning. With the distribution network system harmonic spectrum of the change of the situation is basically consistent, further comparison and analysis of the two methods in the same environment of the early warning speed and error situation is summarized, the specific detection results are shown in Figure 8.

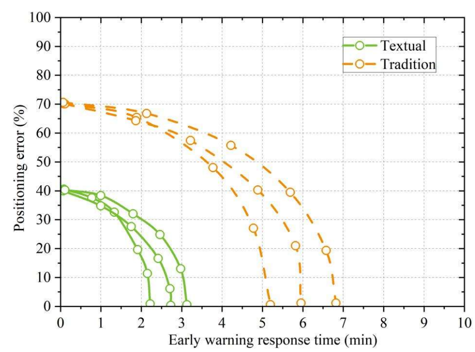


Figure 8: Comparison results of the effectiveness of abnormal early warning

Based on the comprehensive analysis of the comparative detection results in Figure 8, it can be seen that after multiple comparative detection in the same environment, the fault warning response time of this paper's method is significantly faster within 3s, and the error rate of abnormal area localization is significantly reduced and controlled between 0.00% and 40.00%, and the overall performance is significantly better than that of the traditional neural network method. However, due to the limitations of the current technology, the proposed multi-information fusion of distribution system early warning method in the process of practical application still exists a certain error and time delay problems, to be improved subsequently.

IV. Conclusion

In this paper, we propose a new type of sensing method of distribution system state by maintaining the high intensity connection of each node within the distribution system and using Bayesian network algorithm to obtain the real-time state of the distribution system. At the same time, it constructs a multi-source information acquisition and processing framework for the distribution system, fuses multi-dimensional information states, assesses the distribution system operation status and warns of abnormalities. The designed state sensing and fault warning methods show sensitivity and accuracy far beyond similar methods in operation. Among them, the state sensing method can quickly sense 40~50 abnormal data of the distribution system, which is in line with the actual situation, and still maintains high precision sensing ability under different distribution operating states. Compared with similar methods, the fault warning method shows higher warning response sensitivity and fault warning response speed, detecting anomalies within 2s and responding to warnings within 3s, and the error rate of abnormal area localization is lower, only between 0.00% and 40.00%.

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