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Retraction

Retracted: Distribution Network Security Situation Awareness Method Based on the Distribution Network Topology Layered Model

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This article has been retracted by Hindawi following an investigation undertaken by the publisher [1]. This investigation has uncovered evidence of one or more of the following indicators of systematic manipulation of the publication process:

(1) Discrepancies in scope
(2) Discrepancies in the description of the research reported
(3) Discrepancies between the availability of data and the research described
(4) Inappropriate citations
(5) Incoherent, meaningless and/or irrelevant content included in the article
(6) Manipulated or compromised peer review

The presence of these indicators undermines our confidence in the integrity of the article's content and we cannot, therefore, vouch for its reliability. Please note that this notice is intended solely to alert readers that the content of this article is unreliable. We have not investigated whether authors were aware of or involved in the systematic manipulation of the publication process.

Wiley and Hindawi regrets that the usual quality checks did not identify these issues before publication and have since put additional measures in place to safeguard research integrity.

We wish to credit our own Research Integrity and Research Publishing teams and anonymous and named external researchers and research integrity experts for contributing to this investigation.

The corresponding author, as the representative of all authors, has been given the opportunity to register their agreement or disagreement to this retraction. We have kept a record of any response received.

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[1] Y. Ouyang, M. Li, W. Kang, X. Che, and R. Ye, "Distribution Network Security Situation Awareness Method Based on the Distribution Network Topology Layered Model," *Journal of Electrical and Computer Engineering*, vol. 2023, Article ID 6775337, 8 pages, 2023.

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Research Article

Distribution Network Security Situation Awareness Method Based on the Distribution Network Topology Layered Model

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Distribution network security situation awareness refers to the process of perception, understanding, and state projection of systems, elements, and environmental factors within a certain space-time volume. Security situation awareness is an important part of the security assessment of the distribution network. In response to the rapid and accurate distribution network security situation awareness requirements, this paper proposes a distribution network security situation awareness method based the distribution network topology layered model. First, a hierarchical model of the distribution network topology under the premise of optimizing the location of the synchronous phasor measuring device is constructed. This model can quickly capture the system security situation elements. Then, a support vector data description algorithm fused with information entropy is used to realize the identification and understanding of abnormal information in the security situation elements of the distribution network. The long- and short-term memory network is then used to predict the operation trend of the distribution network under normal operation and fault disturbance. Finally, a simulation is established, and the IEEE-33 distribution network model is used to verify the effectiveness of the method proposed in this paper. The results show that the method of this paper improves the speed and accuracy of obtaining the security situation elements of the distribution network, shortens the identification time of the security situation elements, and realizes the security situation awareness of the nodes of the distribution network.

1. Introduction

The distribution network is responsible for the distribution of electric energy in the power system and is an important part of the power system [1–3]. With the development of the social economy and the advancement of power technology, the development of distribution networks is changing with each passing day. The scale of the network is getting bigger and bigger. More and more power distribution equipment is connected, which also brings many problems. The scope of the distribution network is wide, operation management and control are difficult, and the load management at the remote end of the power supply is insufficient [4–6]. The security situation awareness of the distribution network is an important foundation to ensure the safe and reliable operation of the distribution network. It can monitor, analyze, evaluate, and predict the current and future states of the distribution network. As more and more distributed energy sources are connected to the distribution network, it brings great difficulties to the grid's operation, dispatch, and planning [7–11]. Although the current penetration rate of the distributed energy in the distribution network is not high, from the perspective of the long-term development trend of grid energy consumption mode, distributed energy will inevitably become the core source of the grid side. Therefore, the distribution network needs to have sufficient capacity to absorb and control the distributed energy. The traditional theory of distribution network architecture planning based on the load development model needs to be revised, and new planning schemes based on more comprehensive distribution network information will soon be available [12–15].

Situational awareness is the perception, understanding, and prediction of information in the environment during decision-making [16]. Situational awareness is mainly for large or huge dynamic and complex systems with strong uncertainty, and people must intervene in decision-making. It is mainly used in economic, ecological, battlefield, giant network systems, and other fields, including smart grids. In the more advanced stage of the smart grid, under the conditions of the energy Internet, the grid form is more complex, and the access equipment is more diverse. The situational awareness of the grid will face new changes and challenges [17, 18]. Usman and Faruque [19] first proposed the definition of situational awareness, which believed that situational awareness is the operator's perception and synthesis of the dynamic changes of the current equipment and environment in a specific time and space. The authors of [20–23] pointed out that the currently measured data of the phase measurement unit has become a hotspot in the research studies of mining distribution network security issues. It can support the distribution network security situation awareness by collecting a high-precision real-time synchronous measurement data. Xie et al. and Ghaedi and Golshan [24, 25] construct a distribution network anomaly identification method based on the measurement data drive and support vector data tracing, respectively, and analyzes the real-time safe operation status of the distribution network. Given that, the support vector data tracing faces the challenges of a high time-consuming and high space complexity, and its training time increases with the increase of samples [26], especially the introduction of a high-density real-time measurement data collected by the phase measurement unit, which will further increase sample training. The duration is not conducive to the realization of a real-time security situational awareness. Literature [27] pointed out that the distribution network security situation prediction is a very complicated nonlinear change process. Literature [28] compares the ultra-short-term prediction results of regional distribution networks through long- and short-term memory neural networks, support vector regression machines, and progressive gradient regression trees and verifies the superiority of the long- and short-term memory neural network algorithms. The research study on the distribution network security situation awareness method based on the distribution network topology layered model is still to be studied.

Based on the sample training time and prediction accuracy of the distribution network security situation awareness after the phase measurement unit is connected, this paper proposes a distribution network security situation awareness method based on the distribution network topology layered model. Its main contributions are as follows:

(1) To effectively supplement and improve the existing situational awareness methods of the distribution network, under the premise that the economics of the phase measurement unit equipment and the considerable operating state of the distribution network have been considered, the node matrix and the performance of the distribution network phase measurement unit are configured according to the change in the adjacency matrix to construct a hierarchical model of the distribution network topology. The phase measurement unit obtains the real-time system measurement and pseudo-measurement calculation values of the voltage and current of the configuration point and obtains the security situation elements of the whole system.

(2) According to the similarity of the security situation elements of the distribution network, the information entropy theory is introduced, and the entropy threshold is determined. On the basis of the threshold value, the original distribution network security situation elements are processed, and the support vector data tracing algorithm is used to identify the processed distribution of the abnormal information in the elements of the network security situation.

(3) We take the operating status information containing the abnormal information as input, and use the long- and short-term memory neural network algorithms to predict the safe operation trend of the distribution network, and to capture the operation trajectory of the distribution network in the future, so as to provide support for the safety early warning of the distribution network. Finally, a simulation is established to verify the effectiveness of the method in this paper.

The organizational structure of this paper is as follows: Section 2 describes a topology layered model based on the distribution network. The analysis of the security elements of the distribution network, the support vector data description algorithm fused with information entropy, and the prediction of the operation trend of the distribution network based on the long- and short-term memory network are given in Sections 3–5, respectively. In Section 6, a simulation example is provided. Finally, Section 6 gives the conclusion of this paper.

2. Hierarchical Model Based on the Network Topology of Distribution Network

Suppose the total number of nodes in the network is N, the number of phase measurement units is k ($k < N$), the configuration node is a known node, and the phase measurement unit configuration node is used as the root node to expand to the surroundings, then the multiple layers are implemented in a recursive manner and it loops until all nodes in the network are traversed, thus providing the final layering result. The layering steps are as follows:

(1) The system network topology is read and the phase measurement unit configuration node matrix M_1 is obtained:

$$M_1 = \left[m_{i,j}\right]; m_{i,j} = \begin{cases} 1, & j = n_i \\ 0, & \text{other} \end{cases}, \quad i = 1, 2, \cdots, k; j = 1, 2, \cdots, N, \tag{1}$$

where i represents the number of the phase measurement unit device, j represents the node number, and n represents the node number where the i-th phase measurement unit is located.

(2) The adjacent matrix A of the configuration node of the vector measurement unit is obtained:

$$A_m = \left[a_{n_i,j}\right]; a_{n_i,j} = \begin{cases} 1, & j = n_i \text{ or } j = n_i \pm m, \\ 0, & \text{other}. \end{cases} \tag{2}$$

(3) The hierarchical result M of the system network topology is determined:

$$M_{m+1} = M_m \times A_m. \tag{3}$$

(4) The number of nonzero elements L_1 in M_{m+1} is determined. If $L_1 = N$, it means that the hierarchical result contains all the nodes of the system, and we save M_{m+1} as M, and output the hierarchical result as M. If $L_1 < N$, then we update the adjacent matrix A_m in step (2). When updating the adjacent matrix, the condition is met, that is, the node has no adjacent nodes or the condition: the adjacent node of the network node has been stored in M, and the node stops updating.

Through the abovementioned method, the distribution network is hierarchized while ensuring the integrity of the network, which is beneficial to reduce the acquisition time of the real-time security situation elements of the distribution network. The hierarchical modeling process of the distribution network topology is shown in Figure 1.

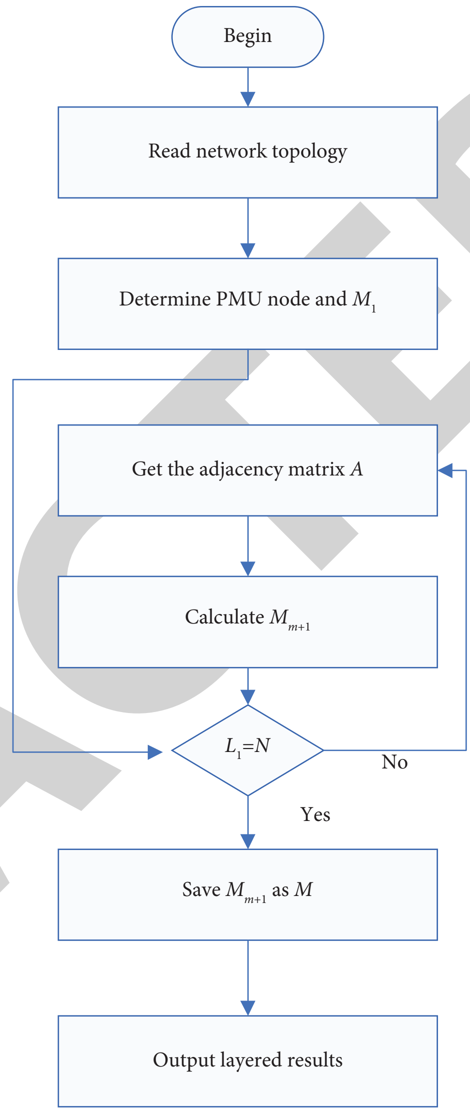

Figure 1: Flowchart of the hierarchical model of the distribution network topology.

3. Analysis of the Elements of the Security Situation of the Distribution Network

The measurement device of the phase measurement unit collects the voltage, current, and the phase angle of the measurement point at a frequency of 60 times per second [29]. Without considering the collection error, based on the hierarchical results of the network topology, the load data of each node of the system and the measurement of the phase measurement unit are used as input values, and the multilayer network is iterated synchronously and in parallel, to reduce the calculation time.

The circuit equivalent circuit diagram shown in Figure 2 can use the real-time measurement data voltage, current, and phase angle of the phase measurement unit at U_i as the situational factor, and can obtain the real-time measured values of U_i and I_i of the voltage and current of the i-th node through model solving. By analogy, the security situation elements of all nodes in the entire network are obtained. The solution steps are as follows:

First, we solve the power distribution of each node. Using the rated voltage of the line, the power distribution of each node is solved successively from the bottom to the top:

$$\begin{cases} S_i' = S_i'' + \Delta S_L = S_i'' + \dfrac{P_i'^2 + Q_i''^2}{U_N^2}\left(R_L + jX_L\right), \\ \\ S_i = S_i' - 0.5\left(B_{i-1,k} + B_{i,k}\right)U_N^2. \end{cases} \tag{4}$$

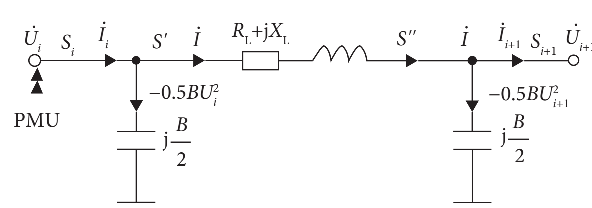

Figure 2: Line equivalent circuit diagram.

Then, we solve the voltage of each node of the system. The voltage at the configuration point of the phase measurement unit is used as the starting node voltage which is then converted into a per-unit value, and the voltage drop of the adjacent nodes is calculated one by one.

$$\dot{U}_i - \dot{U}_{i+1} = \left(R_L + jX_L\right)\dot{I} = \Delta U_i + j\delta U_i, \tag{5}$$

where according to the hierarchical result of the network topology on the basis of the phase measurement unit, as shown in the equivalent circuit diagram in Figure 2, the line voltage drop of each node can be calculated by equation (6) in turn.

$$\begin{cases} \Delta U_i = \dfrac{P_i R_L + Q_i X_L}{U_i}, \\ \\ \delta U_i = \dfrac{P_i X_L - Q_i R_L}{U_i}. \end{cases} \tag{6}$$

We calculate the voltage of each node of the system from equations (6) and (7), and judge whether the error requirements are met according to equation (8), and if so, the iteration will be terminated.

$$\dot{U}_{i+1} = \dot{U}_i - \Delta U_i - \mathrm{j}\delta U_i. \tag{7}$$

$$\max\left\{\dot{U}_{i+1} - \dot{U}_i \mid \right\} < \varepsilon. \tag{8}$$

Finally, according to the line voltage drop value and the node voltage of each layer, each node's phase angle and current phasor are calculated. In the same way, the real-time security situation elements of each node of the system can be obtained.

$$\begin{aligned} d\varphi_{i+1} &= \operatorname{arct}g\frac{P_i X_L - Q_i R_L}{U_i^2 - P_i R_L - Q_i X_L} + \varphi_i \\ \dot{I}_{i+1} &= \frac{S_{i+1}}{V_{i+1}\angle\varphi_{i+1}} n. \end{aligned} \tag{9}$$

4. Support Vector Data Description Algorithm Fused with Information Entropy

4.1. Support Vector Data Description Algorithm. Support vector data description algorithms have been used in many fields. First, it is used for anomaly detection, that is, to detect samples with no typical characteristics in the database; second, it can be used for special classification problems, such as unbalanced and redundant datasets. In addition, it is also used for multiclass classification problems, such as detecting multiple attacks in the network traffic [30]. The support vector data description algorithm is a single classification method on the basis of the boundary data (support vector) description. Its basic idea is to generate a minimum sphere space containing the target data through the training sample points to form a decision boundary. The decision is made according to the distance between the test point and the center during detection, that is, the test point whose distance is less than the radius (it is judged to belong to this category. Otherwise, it is judged as heterogeneous, and the test point closer to the center is judged to be of this category with higher confidence).

4.2. Support Vector Data Description Algorithm Based on the Fusion Information Entropy. Shannon used the uncertainty of event occurrence to measure the amount of information contained in an event in the information theory, that is, the smaller the probability of an event, the more information it contains, and vice versa [31]. The amount of information contained in an event is called the amount of information of the event, and the formula for calculating the amount of information is as follows:

$$H^i = -p^i \log_2 p^i, \tag{10}$$

where p_i represents the probability of the occurrence of event i and H_i represents the amount of information of i.

Information entropy aims to use the degree of uncertainty in the occurrence of discrete events to reflect the average value of the amount of information contained in the information source. The specific expression is as follows:

$$H(X) = -\sum_{i=1}^{n} P(x_i)\log_2 P(x_i), \tag{11}$$

where n represents the number of types of events and $P(x_i)$ represents the probability of occurrence of the i-th event. If the probability of occurrence of n types of events is the same, then $H(X)$ takes the maximum value of 1. Suppose only one type of event has a probability of 1, and the other events do not occur. In that case, $H(X)$ takes the minimum value of 0, H(X). The final training point is selected by comparing the information entropy value. The steps are as follows:

(1) The Euclidean distance between each sample in the kernel space is calculated.
(2) The distance between each sample to evaluate the similarity of the samples is used. If the samples are closer, the similarity between the two will be smaller, or even close to zero. On the contrary, the distance is greater.
(3) Information entropy as a measure of sample similarity is introduced, and the following information entropy evaluation method is adopted.
(4) The threshold is determined.

The entropy value of the sample information in the original training set is used to determine the threshold to reduce the number of samples trained by the support vector data description algorithm and to reduce the training time of the support vector data description algorithm under the premise of ensuring the accuracy.

5. Forecast of Distribution Network Operation Trend Based on the Long- and Short-Term Memory Network

5.1. Long- and Short-Term Memory Network. Compared with the traditional neural network method, the long- and short-term memory network fully considers the influence of the time attribute in the power grid trajectory information on the accuracy of the prediction result. It effectively solves the problem by virtue of its unique internal gate processing structure and the nonlinear transformation process between neuron structures. The disappearance of the gradient in the data fitting process has a good result feedback for the trajectory prediction problem for a long period of time [32].

On the basis of the cyclic neural network, we improved and proposed a long- and short-term memory network method, which can strengthen the memory of key information through the "information chain," which can effectively solve the problem of frequent dependence. The long- and short-term memory network pays more attention to time attribute information in the learning process and combines multiple gate structures inside the long- and short-term memory network neurons to selectively memorize sample information, eliminate redundant information, and strengthen the memory of key features. For the nonlinear fitting problem under multiple time sections, the accuracy of the prediction results is greatly improved compared with the cyclic neural network. Therefore, the long- and short-term memory network can effectively solve the grid data with the characteristics of multisource information interaction in the interconnected large power grid to forecast the problem. The schematic diagram of its internal nodes is shown in Figure 3.

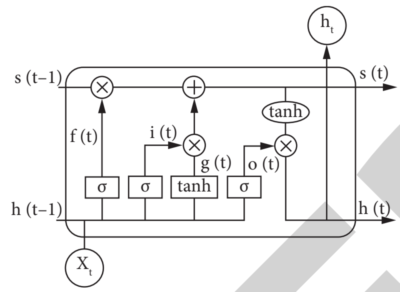

FIGURE 3: Schematic diagram of the internal long- and short-term memory network.

5.2. Distribution Network Based on the Long- and Short-term Memory Network. As shown in Figure 3, in the figure, $X\ (t)$ represents the input sample of the current time section, $h\ (t-1)$ represents the output information of the hidden layer of the memory unit at the previous time, $s\ (t-1)$ represents the previous status information output on the time information chain, and $f\ (t)$, $i\ (t)$, and $o\ (t)$, respectively, represent the output results obtained after the operation of each gate activation function under the current time section. Compared with the neural networks, long- and short-term memory networks can realize the function of identifying the remaining information of the system and can determine the retention of input information, which effectively saves the complexity of prediction and time cost, and is a solution for one of the effective technical means of long-term dependence. Through the abovementioned analysis, it can be seen that the excellent data prediction ability of the long- and short-term memory network mainly depends on the forgetting gate, input gate, output gate, and the added information chain representing the long-term information memory function in the neuron, which is the key to the training and learning process. The useful features can be saved and iterated continuously through this information chain, which effectively guarantees the smooth memory transfer of key information [33].

Different gate controllers in the long- and short-term memory network memory unit correspond to the corresponding activation functions and are responsible for the input information audit function. The specific process can be expressed as input information, the information output by the hidden layer at the previous moment, and the information chain at the previous moment. The information of the iterative transfer process passes through the input gate, output gate, and forget gate at the same time through three gate controllers, and each gate activation function is responsible for auditing and processing the input information. Its long- and short-term memory network model topology is shown in Figure 4.

It can be seen from the figure that the input information and the output information of the hidden layer at the previous moment are collected in the information chain after the activation function of the input gate and the forget gate, and the collected information is obtained after the activation function tanh works with the output information of the output gate, that is, the output information of the memory unit at the current moment. The interaction between the input gate, output gate, and forget gate controllers realize the filtering of input information and the memory function. Through the function of the activation function, the key information can strengthen the memory along the iterative process in the information chain. However, due to too many iterations, the key features of the input information are lost. For complex power system data with multisource, high-dimensional nonlinearity, conventional artificial intelligence technology is difficult to mine the key features hidden in the information trajectory effectively, or the key features are continuously weakened in the continuous iteration process, and effective learning cannot be obtained. The long- and short-term memory network can dig deep into the features in the data and can strengthen the memory through its information chain and special gated equipment, which is of great significance to the development of subsequent data feature extraction.

6. Simulation Analysis

Example 1. This article takes the IEEE-33 model as the research object, and its system configuration scheme is shown in Figure 5. As shown in Figure 5, the phase measurement unit is placed at some nodes to measure the set configuration node's voltage, current, and other measurement information.

Table 1 shows the hierarchical results and real-time security status solution time under the condition of different numbers of phase measurement units in the IEEE-33 distribution network. It can be seen from Table 1 that, under the condition of known phase measurement unit distribution, using the network modeling method proposed in this article, the IEEE-33 system network can be divided into several layers. The increase in the number of PMU configurations in the distribution network can increase the

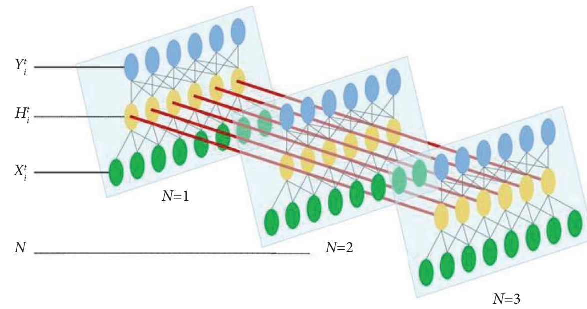

Figure 4: Topology diagram of the long- and short-term memory network model.

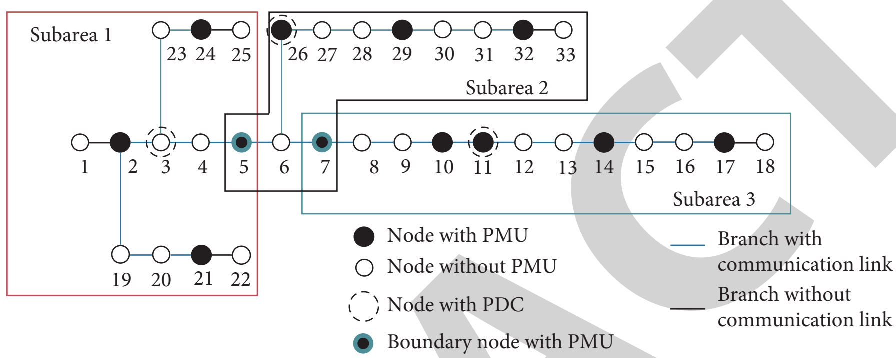

Figure 5: Configuration scheme of the IEEE-33 system.

Table 1: The safe state solution time under the condition of configuring different numbers of phase measurement units.

System	Node number	PMU configuration node area layer number	Solution time (s)
IEEE-33	1, 5, 7	5, 5, 7	0.127
	1, 4, 15, 23, 33	5, 4, 3, 2	0.053
	1, 4, 7, 22, 34	3, 3, 3, 5, 6	0.034
	23, 25, 27, 31	2, 2, 2, 2, 2, 2, 2, 2	0.547
	14, 26, 33, 36	2, 2, 2, 2, 2	0.317

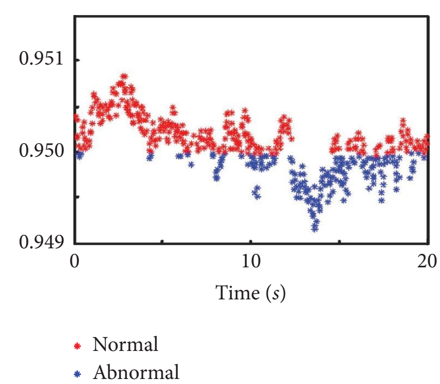

Figure 6: Identification graph of the traditional support vector data description algorithm.

redundancy of system measurement, reduce the number of iteration nodes, and can increase the speed of obtaining safety situation elements.

In addition, when conducting security situational awareness, it is necessary to discern abnormal data in a large amount of operational data. In this paper, the operating data of the voltage amplitude in node 14 in the IEEE-33 system is used as the original input, as shown in Figure 6, for anomaly detection, and the detection time is 7.565 s, respectively. Deleting some equal or similar data in the original voltage amplitude training set can reduce the number of training and shorten the training time without affecting the anomaly detection accuracy. Figure 7 shows a training set obtained after processing the original training set of the voltage amplitude of node 14 in the IEEE-33 system on the basis of the entropy theory. The training time is 1.012 s, and the accuracy is improved to a certain extent. The specific results are shown in Table 2. It can be seen from Table 2 that in IEEE-33, when $\nu = 1$, it is the traditional support vector data description algorithm. The information entropy is not used to process the original training set information. As the value of ν increases, the number of support vectors increases, the calculation time increases, and the accuracy of the support vector data description algorithm identification shows a trend of first increasing and then decreasing, indicating that the support vector data description algorithm when the value of ν is low it is in the "underfitting state," and when the value of ν is high, the support vector data description algorithm is in the "overfitting state." In the IEEE-33 system, ν

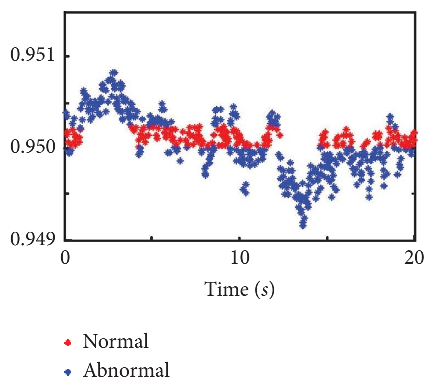

Figure 7: Identification graph of the support vector data description algorithm fused with information entropy.

Table 2: The influence of v value under different distribution networks on the results of the support vector data algorithm.

System	v	Number of support vectors	Calculation time (s)	Accuracy (%)
IEEE-33	0.1	38	0.121	87.853
	0.3	63	0.475	92.354
	0.5	95	0.873	92.576
	0.7	135	1.557	93.755
	0.9	177	2.357	91.173

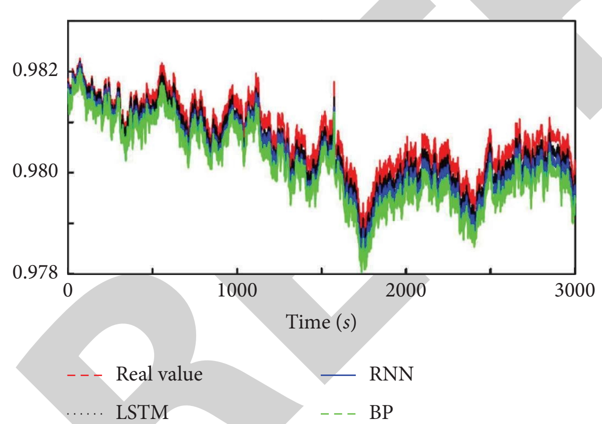

Figure 8: Configuration scheme of the IEEE-33 node system.

has a high accuracy rate in the interval [0.5, 0.7]. It shows that the fusion information entropy support vector data description algorithm model on the basis of the decision coefficient value of this section can better identify the abnormal information in the security situation information, and can improve the system's ability to actively discover potential threats.

LSTM, RNN, and BP neural networks are used to predict the operating trends of different IEEE-33 distribution networks under normal operation and fault disturbances, respectively. The comparison results of the predictions are

Table 3: Comparison of evaluation indicators.

System	Methods	MAE	RMSE	WIs	ENs
IEEE-33	LSTM	0.052	0.021	0.995	0.971
	RNN	0.125	0.105	0.947	0.922
	BP	0.197	0.195	0.899	0.857

shown in Figure 8. It can be seen from Figure 8 that the method used in this paper has obvious advantages.

We use MAE, RMSE, WIs, and ENs indicators to evaluate the accuracy of the IEEE-33 distribution network prediction results, as shown in Table 3. It can be seen from Table 3 that under normal operation and fault disturbance, the prediction accuracy of the operation trend on the basis of LSTM is higher than that of the RNN and BP neural networks. LSTM is better than RNN and BP neural networks in MAE and RMSE indicators, and WIs and ENs indicators are higher than that of the RNN and BP.

7. Conclusion

This paper studies the distribution network security situation awareness method based on the distribution network topology layered model. The hierarchical modeling of the distribution network topology according to the configuration of the phase measurement unit can help the network to achieve a fast and impressive safe operating state and can improve the speed and accuracy of the system's security situation prediction, and can use the information entropy theory to process the original training set of the security situation elements of the distribution network, eliminate similar data, and improve the training efficiency of the support vector data description algorithm. Long- and short-term memory networks are used to predict the safe operation trend of the distribution network. Finally, the IEEE-33 distribution network system with the phase measurement unit device is a typical example of an urban medium voltage distribution network. The safe operation trend prediction is realized based on the phase measurement unit, that is, the security situation awareness function of the distribution network. In the future, considering the topology changes of the distribution network, the security situation needs to be further considered.

Data Availability

The data used to support the findings of the study can be obtained from the corresponding author upon request.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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