Situational Awareness and Fault Warning for Smart Grids Combined with Deep Learning Technology: Application of Digital Twin Technology and Long Short Term Memory Networks

Yanjie Zhang*, Zhihui Kang
Hebi Institute of Engineering and Technology, Henan Polytechnic University, Hebi 458000, China
Email: zhangyanjie2323@126.com
*Corresponding author

Keywords: long short-term memory network, smart grid, deep learning, situational awareness, fault warning, digital twin technology

Received: January 8, 2025

In order to achieve effective perception of the power grid situation and accurate warning of operational faults, this study proposes a situation perception and fault warning method for smart grids based on deep learning technology. Firstly, using the digital twin smart grid platform as a carrier, build a smart grid digital twin situational awareness framework; Secondly, considering both dynamic and static security, intelligent grid situation evaluation indicators are selected; Then, comprehensively analyze the data of various indicators, evaluate the security situation of the power grid, and calculate the security situation assessment value of the power grid; Finally, a smart grid situational awareness model is built based on long short-term memory networks to achieve smart grid situational awareness and fault warning. A provincial-level smart grid big data information platform conducted experiments as the data source. After dividing the training and testing samples, 1000 iterations of learning were carried out to complete situational awareness and fault warning. The experiment was conducted to verify the accuracy, recall, F1 score, fault warning accuracy, fault command response time, and resource consumption of safety situation prediction results and actual values, as well as safety situation discrimination results. The experimental results show that the accuracy of this method for identifying the safety situation of smart grid operation is 98.72%, the recall rate is 98.95%, and the F1 score is 99.06%. This indicates that the comprehensive application performance of this method is good, and it can accurately and effectively perceive, predict, and analyze the safety situation of smart grid operation. At the same time, the maximum fault warning accuracy of this method is 99.82%, the minimum fault command response time is 0.083 s, and the minimum resource consumption is 118.57 MB, indicating that this method has a good power grid fault warning effect, which can accurately distinguish between normal operating conditions and critical states before faults and provide real-time and effective warnings.

Povzetek: Raziskava predstavi metodo za zaznavanje situacijskega zavedanja in napovedovanje napak v pametnih omrežjih, ki temelji na globokem učenju z uporabo omrežij dolgoročne kratkoročne pomnilnosti (LSTM) in digitalne tehnologije dvojčkov.

1 Introduction

The smart grid, known as the new era of “Grid 2.0”, is rooted in the solid foundation of integrated and high-speed bidirectional communication networks [1]. With cutting-edge sensing and measurement technology, precision equipment technology, advanced control strategies, and the comprehensive application of intelligent decision support systems, it is committed to achieving the reliability, safety, economy, high efficiency, environmental harmony, and worry free safety of power supply for users [2]. With the rapid development of the power industry, China has entered an era of “ultra-high voltage, large power grid”. However, the structure of the smart grid is relatively weak, and the failure rate of electrical equipment and lines is high. It has also experienced multiple large-scale power outages [3]. Therefore, it is necessary to timely and effectively prevent power outages in the power grid, predict the safe operation status of the smart grid, and perceive the safety situation of the smart grid.

Presekal et al. [4] proposes a hybrid deep learning model based on the perspective of smart grid network security situational awareness to achieve online network attack situational awareness. By combining deep convolutional neural networks to construct a basic perception network framework, a temporal data classification unit is constructed in the network architecture to detect anomalies in the input power grid situation data. However, this method has the problem of slow overall response speed to safety faults. Bai et al. [5] extensively explores effective security situational awareness methods and remote operation and maintenance technologies to enhance the overall defense capability of smart grid systems, ensure power supply continuity and reliability. Constructing a neural network model using radial basis functions to comprehensively process operational data of the power grid system. On this basis, linear discriminant analysis was introduced into the model to establish an efficient power grid anomaly situation detection model, effectively realizing the perception of smart grid operation trends. However, this method has certain room for improvement in the division of power grid operation risk thresholds. Gong et al. [6] proposes a network security situational awareness detection technology based on distributed data analysis, taking into account the characteristics of big data in intelligent power networks. By applying cross entropy function and linear units, the loss evaluation part of the neural network model was optimized, and an innovative smart grid operation situation awareness model was constructed by integrating improved linear unit structure. However, this method has the problem of low utilization of computational resources. Zhai et al. [7], an iterative algorithm that integrates Gaussian processes was designed to use the time series measured by the phasor measurement units of the actual power grid to verify the trend indicators of power grid operation online, in order to evaluate the stability level of smart grid operation. However, the overall safety situation awareness accuracy of this method needs to be improved.

Long Short Term Memory (LSTM), as a special variant of recurrent neural networks, is an efficient deep learning technique with strong sequential data processing capabilities, suitable for processing time-series data and predicting future situations. Due to the large and complex amount of data involved in the smart grid, including multiple dimensions and variables, many important states and changes may accumulate over time and affect future trends. Based on the above analysis, this study combines deep learning technology to propose a smart grid situational awareness method based on LSTM, and further designs a smart grid fault warning method with the aim of reducing the impact of operational faults.

2 Design of smart grid situation awareness and fault warning methods

2.1 Construction of smart grid digital twin situation awareness framework

Smart grid digital twin refers to the complete mapping of the physical entities of the smart grid in the digital world based on digital twin technology, forming a digital model that is synchronized and consistent with the real grid. This digital model can include all information about the equipment, lines, operating status, environmental factors, etc. of the power grid, achieving real-time monitoring and prediction of the power grid status.

The digital twin power grid essentially belongs to the form of a physical power grid coexisting with a virtual power grid in the information dimension, and the integration of virtual and real power grids [8, 9]. Therefore, the collection of smart grid situation indicator data can be based on the digital twin grid. On the basis of smart grid IoT data perception and multi-dimensional information transmission, real-time holographic simulation can be carried out through the digital Lisheng platform to make scientific decisions and intelligent control processes, and to achieve real-time prediction and analysis of the operation situation of the physical grid. The smart grid digital twin situational awareness framework is shown in Figure 1.

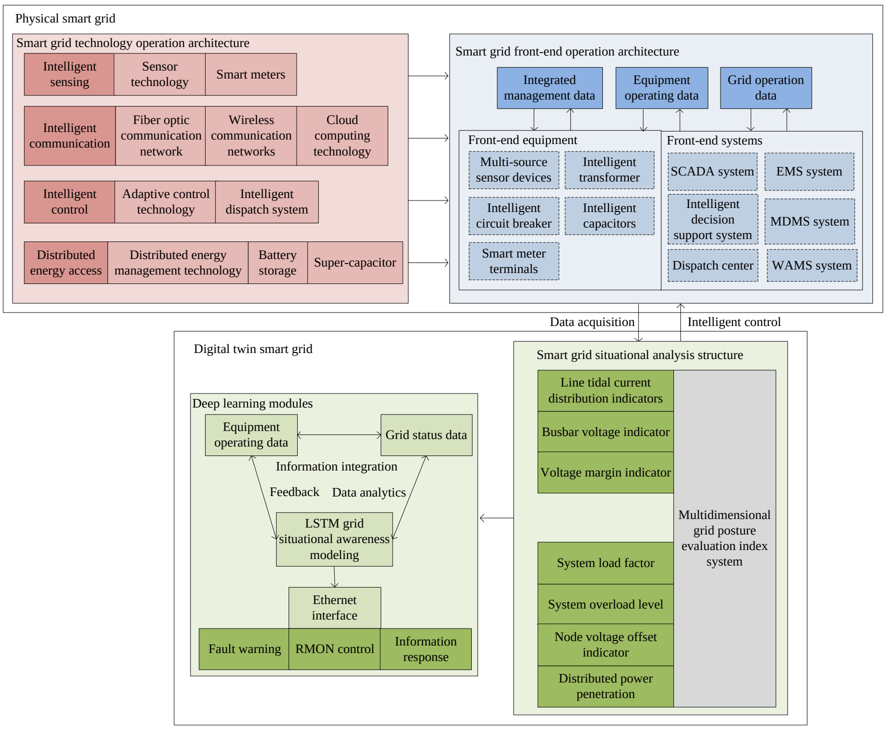


Figure 1: The digital twin situational awareness framework of smart grid

The smart grid digital twin situational awareness framework covers multiple elements. At the physical entity level of the smart grid, real-time collection of operational and management data and other status information of the smart grid and its internal devices, such as smart meter data and device operating parameters, is achieved through technology entities such as sensors and wireless communication. This information is transmitted to the digital twin through a digital twin link. The digital twin initially processes the received data and constructs a multidimensional power grid situation evaluation index system [10], including indicators such as line flow distribution and bus voltage. Then, based on this, the situation evaluation index data is filtered and generated, and transmitted to the deep learning unit through the digital twin data platform. The operational architecture of smart grid technology in the framework includes intelligent sensing, communication, control, and distributed energy access; The front-end operation architecture includes comprehensive management, equipment and power grid operation data related content, as well as various front-end devices and systems. The deep learning module uses LSTM situational awareness modeling and other methods to analyze data based on power grid status data, achieving intelligent power grid situational analysis functions. It also has response mechanisms such as fault warnings.

2.2 Selection of evaluation indicators for smart grid situation

Situational awareness refers to the recognition and understanding of environmental factors within a certain time and space range, and the prediction of future development trends. The situational awareness of smart grid is an important technical means to grasp the operation trajectory of the power grid. In the perception practice, it is necessary to first monitor and extract various factors related to the changes in power grid operation, in order to characterize the operation trajectory of the power grid.

However, a single indicator cannot effectively characterize the operational trajectory of the smart grid. Therefore, based on the analysis structure of the smart grid situation using the correlation indicators in Figure 1, this article considers both dynamic and static security aspects of the smart grid, and sets the line flow distribution index P_1', bus voltage index P_2', and active power margin P_3' as the dynamic security situation evaluation indicators for the smart grid, which can reflect the operating status of the smart grid; The system load rate Q_1', system overload degree Q_2', node voltage offset index Q_3', and distributed power penetration rate Q_4' are static security situation assessment indicators, which perceive and analyze the situation of the smart grid. Based on the evaluation indicators and related parameters, the data collection scope is clarified, and the corresponding collection indicator data is collected to comprehensively and effectively evaluate the operation trajectory of the smart grid.

Among them, the power flow distribution index of the line refers to the average difference between the maximum transmission capacity allowed by the line in the system and the active power flow of the line. This indicator reflects the stability of the system. The larger the indicator value, the farther the system is from the allowed maximum transmission capacity and the more stable the system is. The expression for this indicator and its associated parameters is Equations (1) and (2):

$$P_1' = V_z' \times \left(I_{za}'\right)^{\overline{Z}} \tag{1}$$

$$V_z' = \frac{I_{za} \times \cos\left(\hat{\theta}_z - \varphi_1\right)}{p_{za}'} \tag{2}$$

In the formula: V_z' represents the phasor of the bus phase voltage; za represents the branch bus in the smart grid, and I_{za}' represents the parallel double bus structure, which is the phasor of the line current generated during the load transfer process of the double bus; $\overline{Z}$ represents conjugate complex numbers; p_{za}' represents the active power of the three-phase AC line in the smart grid; $\hat{\theta}_z$ represents the voltage phase angle; φ_1 represents the phase angle of the current.

The amplitude of bus voltage refers to the average value of the voltage of the bus (excluding the bus connected to the generator) in the system. This indicator reflects the ability of the system bus to withstand voltage. The larger the indicator value, the stronger the system's ability to withstand voltage [11, 12]. Based on the known power flow distribution of the line, calculate the bus voltage amplitude index and related parameters according to the active power of the line where the parallel bus is located Equation (3):

$$P_2' = X_{z,\gamma_1}'\left(V_z' + V_a'\right)^2 + 2\left[R_{za}'\left(p_{za}' + q_{za}'\right)\right] \tag{3}$$

In the formula: X_{z,γ_1}' represents the reactance between the distributed generation unit of the smart grid and the busbar; γ_1 represents the power generation unit, which is a synchronous generator; V_a' represents the phase voltage phasor of the branch bus in the double bus structure; R_{za}' represents the resistance of the three-phase AC line in the smart grid; q_{za}' represents the reactive power of the three-phase AC line in the smart grid [13].

The active power margin refers to the average ratio of the difference between the maximum transmission capacity of the line in the system and the active power flow of the line in the current state. This indicator reflects the system's ability to withstand power disturbances, and the larger the indicator value, the stronger the system's ability to withstand power disturbances [14]. Given the layout of distributed generation units in the three-phase AC line of a smart grid, and based on clarifying the reactance parameters between the distributed generation units and the bus, calculate the active power margin of the smart grid system, as shown in Equations (4) and (5):

$$P_3' = P_2'(\lambda_1 - \lambda_2) \quad (4)$$

$$\lambda_2 = \sum_{m'=1}^{2} \sin\delta' \times \hat{E}(V_z' + V_a')^{m'} - X'_{z,\gamma_1} \quad (5)$$

In the formula: λ_1 and λ_2 represent the total active power generation capacity and total active load demand of the smart grid system; m' represents the total layout of power generation units in the power grid system; δ' represents the power angle of the power generation unit, which is the phase difference between the excitation potential and the terminal voltage of the generator; $\hat{E}$ represents the electromotive force of the generator.

Based on the static security of the smart grid, the system load rate refers to the ratio of the sum of the transmission power of the system lines to the maximum transmission capacity allowed by the lines. This indicator reflects the probability of a major power outage in the system, and the higher the value of this indicator, the greater the probability of a major power outage occurring in the system [15]. The degree of system overload refers to the ratio of the number of overloaded lines to the total number of remaining lines when a component of the system fails. This indicator represents the degree of overload caused by system component failures. The larger the value of this indicator, the more lines the system deviates from normal state, and the greater the degree of overload of the system, making its state more dangerous. The expression for this indicator and its associated parameters is Equations (6) and (7):

$$Q_1' = \lambda_2 - \left\| C_{i'}' - \sqrt[\lambda_1]{\vec{p}_1} \right\| \quad (6)$$

$$Q_2' = \frac{n_2}{n_1(n_1+1)} \quad (7)$$

In the formula: $C_{i'}'$ represents the required capacity of the generator; n_1 and n_2 represents the total number of lines in the smart grid system and the total number of overloaded lines in the system; $\vec{p}_1$ represents the total load power of the power grid.

The node voltage offset index Q_3' refers to the sum of the difference between the node voltage of the current system and the node voltage under normal conditions. This indicator reflects the volatility of the system voltage. The larger the value of this indicator, the greater the deviation of the system voltage from the normal voltage, and the more dangerous the system is. Considering the diversity and nonlinear characteristics of this indicator, only its characterization features will be analyzed here.

In addition, the penetration rate of distributed power refers to an indicator that measures the proportion of distributed power in the smart grid, reflecting the scale of distributed power relative to the total load of the grid, and quantitatively reflecting the degree of penetration of distributed power in the entire smart grid system. As the penetration rate increases, the impact of fluctuations in distributed power sources on grid frequency will gradually increase. At this time, new frequency regulation strategies (such as the coordination of energy storage systems) are needed to ensure grid frequency stability. This indicator also verifies the matching degree between the connected distributed power sources and local loads. The expression for this indicator and its associated parameters is Equation (8):

$$Q_4' = \frac{\sum_{j=1}^{\tilde{n}} \vec{p}_j(\tilde{n}+1)}{\vec{p}_1} \quad (8)$$

In the formula: $\tilde{n}$ represents the number of distributed power sources in the smart grid; j represents the index of the power supply unit; $\vec{p}_j$ represents the output power of a fixed sequence distributed power source.

2.3 Smart grid situation awareness and fault warning based on long short term memory networks

2.3.1 Smart grid situation assessment

By comprehensively analyzing various indicator data, evaluate the safety situation of the power grid and calculate the safety situation assessment value of the power grid. Firstly, in order to improve the convenience of indicator processing and eliminate errors in indicators, dynamic and static security indicators are regarded as an analytical subject, and each indicator is normalized Equation (9):

$$L = (k_o - \min\, k_o)(\max k_o - \min\, k_o)^{-1} \quad (9)$$

In the formula: L represents the comprehensive indicator of the power grid situation after the unified state analysis subject; k_o represents the o -th indicator value of the smart grid system.

Secondly, based on the Analytic Hierarchy Process, determine the weight coefficients of the corresponding indicator values in Equation (9). By repeatedly determining the weight coefficients of multiple indicators and multiplying the comprehensive indicator data with the corresponding weights, the smart grid security situation assessment value is calculated Equation (10).

$$\hat{\kappa} = \sum_{o=1}^{7} \varpi_o \times L \quad (10)$$

In the formula: $\hat{\kappa}$ represents the evaluation value of the security situation of the smart grid; ϖ_o represents the weight coefficient corresponding to specific indicator data.

According to the safety standards for the operation of smart grids, further refine the risk categories corresponding to the security situation assessment values of smart grids, and set reasonable warning thresholds for the comprehensive indicators of security situation. The threshold and risk level classification of smart grid security situation warning is shown in Table 1.

Table 1: Threshold and risk level of smart grid security situation warning

Indicator warning thresholds	Risk class	Description of the type of situational risk
0-0.2	Safety status	——
0.21-0.5	Early warning status (low risk)	There are small fluctuations in the power of the distributed power sources, but the power supply is stabilizing the transmission efficiency of some lines slightly below optimal.
0.51-0.8	Dangerous state (medium risk)	Risk of overloading of transformers, small deviations from the normal range of voltage in some areas, abnormal intermittent changes in distributed power.
0.81-1.0	Emergency status (high risk)	Multiple key devices are close to or have reached their limit operating conditions, localized power outages, the grid control system is unable to accurately obtain information on the status of the devices, and there is a power deficit in the grid.

The division of the warning threshold for smart grid security situation in Table 1 above is based on a deep understanding of the operating characteristics of the power grid, statistical analysis of actual operating data, and comprehensive consideration of power grid security standards. Taking 0-0.2 as an example to represent the safety status, selecting 0.2 as the upper limit is based on statistical analysis of historical operating data and comprehensive consideration of power grid safety standards. This value ensures that the power grid can maintain safe and stable operation in most cases. If the threshold is set too loosely, it may reduce the sensitivity and accuracy of the warning system, thereby increasing the risk of power grid operation.

2.3.2 Analysis of long short term memory network structure

Long Short Term Memory (LSTM), as a special variant of recurrent neural networks, is a deep learning technique with strong sequential data processing capabilities, suitable for processing time-series data and predicting future situations [16, 17]. LSTM network introduces a unique gate structure (input gate, forget gate, and output gate) based on traditional recurrent neural networks, and then captures and models long-term dependencies in time series data through memory units and gate structures [18-21].

The integration of digital twin technology and LSTM significantly enhances the situational awareness and fault warning capabilities of smart grids through dynamic modeling and real-time updates. The digital twin technology constructs a virtual model of the power grid that can reflect the operating status in real time, while LSTM, as a time series model, excels at capturing long-term dependencies and complex nonlinear patterns in power grid data. This combination not only improves the accuracy of fault prediction, but also reduces false alarm rates, while enhancing adaptability, allowing it to dynamically adjust according to the real-time status of the power grid. Compared to traditional methods, LSTM performs better in processing time series data and can more effectively identify potential faults.

As for why other models (such as GRU or transformer models) are not considered, it is mainly due to their limitations in applicability and efficiency in smart grid scenarios. Although GRU is a simplified version of LSTM, its modeling ability is not as good as LSTM when dealing with complex time series data, especially in capturing long-term dependencies. Although the transformer model performs well in certain tasks, its computational complexity is high and it requires large-scale data for training, making it difficult to meet the real-time processing requirements of smart grids. In addition, LSTM has been widely applied in time series tasks, and its performance and stability have been fully verified. However, GRU and transformer models have relatively few applications in the field of smart grids, lacking sufficient practical support. Therefore, LSTM has become the preferred model in this scenario.

The data involved in the smart grid is massive and complex, containing multiple dimensions and variables, and many important states and changes may accumulate over time and affect future trends. LSTM, as a special variant of recurrent neural networks, has strong sequential data processing capabilities and is suitable for processing time-series data and predicting future situations. By introducing unique gate structures (input gate, forget gate, and output gate), LSTM can capture and model long-term dependencies in time series data, effectively improving the accuracy of situation prediction. In addition, the smart grid digital twin situational awareness framework constructed with digital twin technology can comprehensively and real-time monitor the status of the power grid, providing accurate and comprehensive input data for LSTM, further improving the accuracy of situational awareness and fault warning. Therefore, the article selects it as the main carrier for power grid situational awareness prediction, which is based on LSTM network for smart grid situational awareness. LSTM network structure is shown in Figure 2.

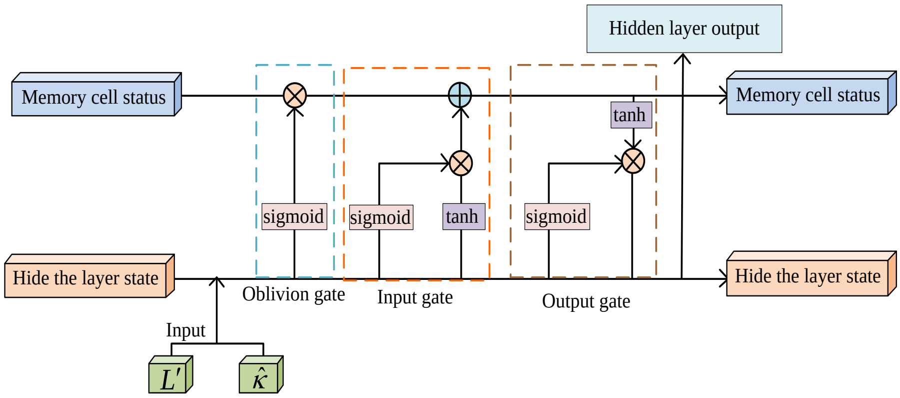


Figure 2: LSTM network architecture

In this study, the optimizer used in the LSTM network is the Adam optimizer, which can adaptively adjust the learning rate, accelerate convergence, and improve training efficiency. Set the learning rate to 0.5 to reduce overfitting. Set the batch size to 64 to balance memory usage and training speed. To better balance model complexity and learning ability, two hidden layers were chosen.

As shown in Figure 2, the basic unit of LSTM network includes three gates, namely input gate, forget gate, and output gate. Among them, the forget gate determines which information will be forgotten from the unit state, and its calculation Equation (11):

$$\hat{F}_1 = \sigma_1[\vec{\varpi}_1(y_{T-1}, L)(y_{T-1}, \hat{\kappa}) + b_1] \qquad (11)$$

In the formula: $\hat{F}_1$ represents the forget gate output at a specific time step; σ_1 represents the sigmoid activation function; $\vec{\varpi}_1$ represents the forgetting gate weight matrix; y_{T-1} represents the hidden state of the previous time step; T represents the current time step; b_1 represents the bias coefficient of the forget gate.

The input gate consists of two parts: the sigmoid layer and the tanh layer. The sigmoid layer determines which values will be updated, while the tanh layer creates a new candidate value vector. The calculation is Equation (12):

$$\begin{cases} \hat{F}_2 = \sigma_1[\vec{\varpi}_2(y_{T-1}, L)(y_{T-1}, \hat{\kappa}) + b_2] \\ \vec{H}_0 = \sigma_2[\vec{\varpi}_0(y_{T-1}, L)(y_{T-1}, \hat{\kappa}) + b_0] \end{cases} \qquad (12)$$

In the formula: $\hat{F}_2$ represents the input gate output at a specific time step; $\vec{\varpi}_2$ represents the weight matrix of the input gate; b_2 represents the bias coefficient of the input gate; $\vec{H}_0$ represents the candidate unit state at a specific time step; σ_2 represents the tanh activation function; $\vec{\varpi}_0$ represents the weight matrix of candidate unit states; b_0 represents the bias coefficient of the candidate unit state.

The output gate determines the output of the next hidden state, which is specifically represented as Equation (13):

$$\hat{F}_3 = \sigma_1[\vec{\varpi}_3(y_{T-1}, L)(y_{T-1}, \hat{\kappa}) + b_3] \qquad (13)$$

In the formula: $\hat{F}_3$ represents the output gate output at a specific time step; $\vec{\varpi}_3$ represents the output gate weight matrix; b_3 represents the bias coefficient of the output gate.

2.3.3 Implementation of smart grid situation awareness and fault warning

On the basis of laying out the LSTM model, it is necessary to train the network model and combine the trained model with the dynamic and static characteristics of the smart grid situation, and deploy it to the smart grid system [22, 23]. The specific model training steps are as follows:

Step 1: Input data partitioning. Using the normalized index data from the previous cycle (previous time step) as input and training data for LSTM, these normalized index data cover multiple dimensions of dynamic and static security of smart grids. Subsequently, these data are scientifically divided into training and testing sets. Typically, the training set is used for model training and learning, while the testing set is used for model performance validation, ensuring that the model can generalize to unseen data.

Step 2: Build an LSTM network. Based on the characteristics of the smart grid situation indicator data, the number of input layer feature types in the LSTM network structure is set to 7, and the number of hidden layers is set to 2, in order to balance the complexity and learning ability of the model. This network architecture design aims to efficiently extract key information from input data, laying a solid foundation for subsequent security situation assessment and fault warning.

Step 3: Initialize network parameters. After the LSTM network is built, the weights and biases in the network are randomly initialized to ensure that the model has sufficient diversity at the beginning of training, so as to gradually converge to the optimal solution in the subsequent learning process. This study sets the weight to 0.5 and the bias to 0.1.

Step 4: Model training. Using the training set data for forward propagation, calculate the loss function to measure the difference between the current model's predicted results and the true values. Subsequently, the weights and biases in the network are updated using backpropagation algorithm, gradually reducing the value of the loss function. This process is repeated in multiple iterations until the performance of the model on the training set reaches stability.

Step 5: Performance evaluation. Evaluate the performance of the trained LSTM model through a test set. The evaluation indicators include accuracy, recall, and F1 score, which can comprehensively reflect the model's ability in safety situation assessment and fault warning. Based on the evaluation results, continuously adjust the network structure and hyperparameters (such as learning rate, number of hidden units, etc.) to optimize the model performance. This process may require multiple iterations until the model performance reaches the predetermined accuracy and reliability standards [24-26].

Step 6: After the LSTM network model completes training and meets the predetermined performance standards, deploy it to the smart grid system. The model can receive real-time operation data of the smart grid and output evaluation scores from multiple dimensions including power flow distribution of grid lines, system load, and power penetration rate. These evaluation scores constitute the security situation assessment values of the smart grid, which can be compared with the preset alarm threshold to determine whether the operating situation of the smart grid is in a fault abnormal state.

Step 7: Based on the alarm threshold, corresponding level, and output evaluation value in Table 1, compare them to determine whether the operation status of the smart grid is in a fault abnormal state, and achieve smart grid situation perception and fault warning.

3 Experiments and results analysis

3.1 Experimental environment construction

In order to verify the feasibility and effectiveness of the method proposed in this article, real-time data from a provincial smart grid big data information platform in October was used as the experimental object, and a real-time data set size of 125 GB was collected. On this basis, the collected data is divided based on the power simulation system, generating a total of 120 power grid situation evaluation indicators including line flow distribution indicators, bus voltage indicators, active power margin, system load rate, system overload degree, node voltage offset indicators, distributed power source penetration rate, etc. (each data includes all power grid situation evaluation indicators). The specific number of generated indicators is as follows:

(1) Dynamic security situation assessment indicators: 15 data points on line flow distribution indicators; 12 pieces of bus voltage indicator data; 23 active power margin data;

(2) Static security situation assessment indicators: 18 system load rate data; 21 pieces of system overload degree data; 16 pieces of node voltage offset index data; 15 pieces of penetration rate data for distributed power sources.

In the experimental analysis process, the generated data will be used as samples for the security situation assessment of the smart grid system. Each piece of data corresponds to one sample, for a total of 120 samples. In order to ensure the generalization ability of the model and avoid overfitting, it is necessary to retain a portion of the data for testing. Therefore, this study selected approximately 70% (85 samples) as training samples and approximately 30% (35 samples) as testing samples.

For the sample data, first, normalization is performed to treat dynamic and static security indicators as one analysis subject. Normalize each indicator to eliminate indicator errors and form a unified comprehensive indicator of the power grid situation. Then, the Analytic Hierarchy Process is used to determine the weight coefficients of each indicator value. By repeatedly determining the weight coefficients of multiple indicators, the comprehensive indicator data is multiplied with the corresponding weights to calculate the results of the security situation assessment of the smart grid.

Preprocess the power grid situation evaluation index data in the test samples using the comprehensive index generation method described in the article. During training, randomly select a fixed number of samples in each iteration to form a small batch dataset for training until the preset number of iterations is reached. The configuration information of the software and hardware devices included in the experimental environment is shown in Table 2.

Table 2: Configuration information of experimental software and hardware equipment

Type of experimental equipment	Device model	Performance parameters/running version
Hardware equipment	PowerEdge R740 server	Processor: 20 cores, 40 threads, base frequency 2.3 GHz, max RWD 3.9 GHz. Memory: Supports up to 1.5 TB of DDR4 memory. Storage: Equipped with multiple hard disks 8 x 1TB SAS hard disks in a RAID array.
	KC705 FPGA development board	Logical Resources: The number of LCs is about 326,000 and the number of CLBs is about 40,750.

		Storage Resources: Total BRAM capacity is 18.5 Mb.
Software equipment	Linux operating system	Ubuntu 18.04 LTS
	Python programming language	Python 3.7
	TensorFlow deep learning framework	TensorFlow 2.3

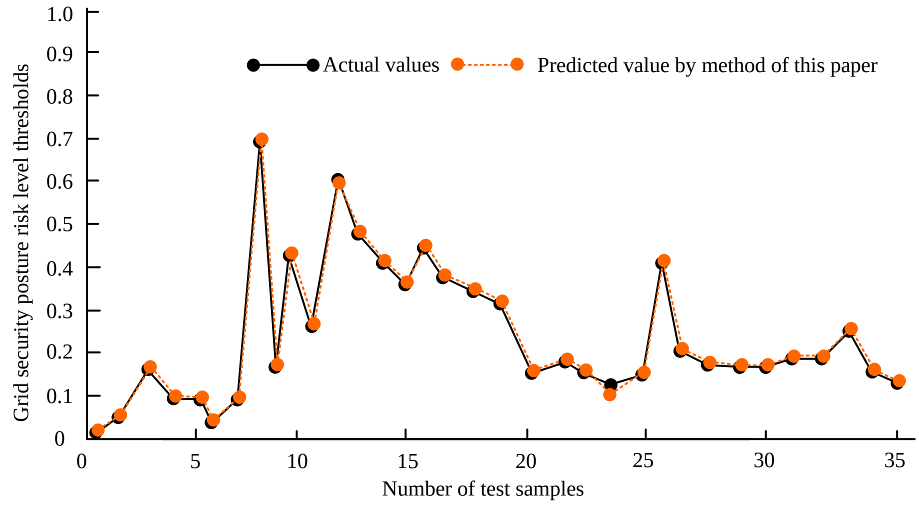
The experimental simulation parameters are shown in Table 3.

Table 3: Experimental simulation parameters

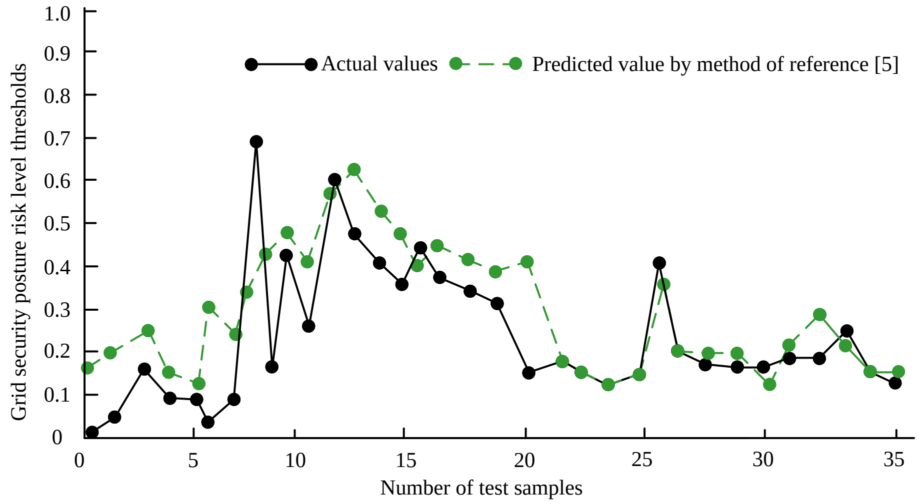
Simulation parameters	Parameter value
Input data time step	120
Output data time step	1
Number of hidden layers of LSTM network	2
Number of hidden units	128
Hidden layer activation function	tanh function
Learning rate	0.5
Number of iterations	1000

3.2 Testing the effect of smart grid security situation awareness

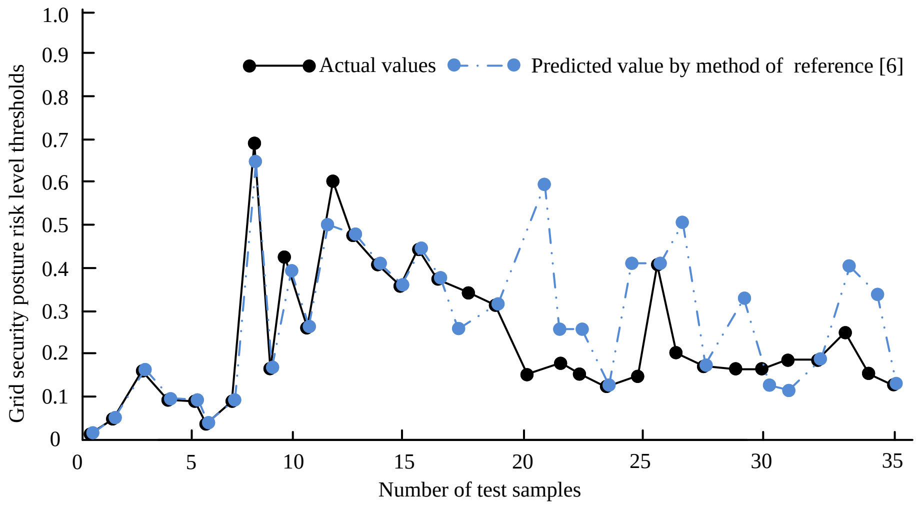
In order to verify the practical application effect of method of this paper in intelligent network security situational awareness and analysis, method of reference [5] and method of reference [6] were introduced as comparative methods, both of which were trained and learned 1000 times, and then predicted on the test samples. Based on the warning threshold and risk level of smart grid security situation in Table 1, the predicted value of the test sample is defined as the warning threshold range of smart grid security situation risk level. Compare the predicted values of the obtained test samples with the actual values to verify the effectiveness of the smart grid security situation prediction. The specific results are shown in Figure 3.



(a) Method of this paper



(b) Method of Bai et al. [5]



(c) Method of Gong et al. [6]

Figure 3: Test results of the perception effect of smart grid security situation (P-values<0.05)

As shown in Figure 3, using the method of this paper to predict the security situation of the smart grid for the test samples, the predicted results (i.e., the warning threshold corresponding to the risk level of the samples) are consistent with the actual values, and the overall fit is high. There is no situation where the predicted risk level deviates from the actual value. However, the overall fit between the predicted results obtained using the method of Bai et al. [5] and method of Gong et al. [6] and the actual values of the test samples is low, and there is a significant deviation between the predicted results and the actual values regardless of the risk threshold of the test samples. Although the method of Bai et al. [5] constructs a neural network model using radial basis functions and combines linear discriminant analysis to detect abnormal situations in the power grid, there are certain shortcomings in the division of risk thresholds for power grid operation. This may make it difficult for the model to accurately classify certain critical data points when judging the operation status of the smart grid, thereby affecting the overall prediction accuracy. Although the method of Gong et al. [6] combines the characteristics of big data in intelligent power networks and proposes a network security situational awareness detection technology based on distributed data analysis, there are still shortcomings in terms of computational resource utilization. This may limit the performance of the model when processing large-scale, high-dimensional data, resulting in a certain deviation between the predicted results and the actual values [27-29].

From this, it can be seen that using the method of this paper can more accurately capture the changing trends of the smart grid situation, predict the risk level of data security situation better, effectively achieve smart grid security situation awareness, and provide more reliable basis for the scheduling and operation of smart grids.

3.3 The effectiveness of identifying the safety situation of smart grid operation

In order to verify the effectiveness of the method of this paper in discriminating the operating situation of smart grids, based on the experimental environment in section 3.2, the accuracy of different methods in discriminating the operating situation of smart grids was analyzed. However, considering that different methods may have inconsistent dimensions in extracting data features. Therefore, when the experimental environment is unified into the same feature quantity (analyzed according to the percentage of training samples to the total sample size), accuracy, recall, and F1 score are used as evaluation indicators to analyze the accuracy of various methods for predicting the safety situation of smart grid operation. The specific results are shown in Table 4.

Table 4: The recognition effect of the safety situation of smart grid operation (P-values <0.05)

Grid situational awareness algorithm	Accuracy/%	Recall rate/%	F1 score/%
Method of this paper	98.72	98.95	99.06
Method of Bai et al. [5]	89.32	90.01	90.93
Method of Gong et al. [6]	90.26	91.74	92.18

According to Table 4, the accuracy of using the method of this paper for identifying the safety situation of smart grid operation is 98.72%, the recall rate is 98.95%, and the F1 score is 99.06%. This indicates that the algorithm has high risk prediction accuracy for smart grid safety situation operation data based on unified feature quantities, and its application is relatively stable. The obtained prediction accuracy numerical results are superior to those obtained by the method of Bai et al. [5] and method of Gong et al. [6]. Due to the inadequacy of the method of Bai et al. [5] in dividing the risk threshold for power grid operation, the model may have misjudgments or omissions in identifying the safety situation of smart grid operation, thereby reducing accuracy and recall. Meanwhile, this deficiency may also affect the performance of F1 scores. The shortcomings of the method of Gong et al. [6] in terms of computational resource utilization may limit the performance of the model when dealing with complex data. This may lead to poor performance of the model in feature extraction, classification prediction, and other aspects, thereby affecting the overall accuracy, recall, and F1 score.

From this, it can be seen that the overall performance of the method of this paper is good, which can accurately and effectively perceive, predict, and analyze the safety situation of smart grid operation.

3.4 Analysis of the effectiveness of smart grid fault warning

During the simulation testing process of smart grid situational awareness and fault warning, a total of 1000 iterations were executed. In order to further verify the effectiveness of smart grid fault warning, the number of iterations to be executed will be uniformly divided into 5 planning units. Each unit calculates the accuracy of fault warning, response time of fault command, amount of resources consumed (all average values during the iteration process) generated by method of this paper, method of Bai et al. [5], and method of Gong et al. [6] during 200 iterations to verify the effectiveness of intelligent power grid fault warnings. Among them:

(a) Accuracy of fault warning: This indicator is the core standard for measuring the performance of smart grid fault warning methods. It represents the proportion of correctly predicted faults and issuing warning signals. High accuracy of fault warning means that the fault warning method can accurately distinguish between normal operating conditions and critical states before faults, providing strong guarantees for the safe and stable operation of the power grid.

(b) Response time of fault command: This indicator reflects the speed at which smart grid fault warning methods issue warning instructions after detecting faults. A shorter response time for fault instructions means that the fault warning method can respond to faults faster, buying valuable time for subsequent fault handling.

(c) Amount of resources consumed: This indicator measures the computational resources and storage space required for the operation of smart grid fault warning methods. Lower resource consumption means that fault warning methods can operate in a more economical way, reducing operational costs.

The specific test results of the intelligent grid fault warning effect are shown in Table 5.

Table 5: Smart grid fault warning effectiveness (P-values <0.05)

Experimental indicators	Iterations/times	Method of this paper	Method of Bai et al. [5]	Method of Gong et al. [6]
Accuracy of fault warning/%	200	98.12	88.34	90.42
	400	98.45	88.65	91.27
	600	98.96	90.03	91.39
	800	99.16	91.26	91.87
	1000	99.82	91.38	92.08
Response time of fault command/s	200	0.096	0.089	0.098
	400	0.085	0.098	0.107
	600	0.074	0.105	0.112
	800	0.091	0.107	0.101
	1000	0.083	0.112	0.118
Amount of resources consumed/MB	200	125.36	152.65	150.16
	400	123.28	153.78	155.79
	600	120.54	153.96	160.24
	800	119.16	155.02	161.77
	1000	118.57	155.28	168.56

According to Table 5, as the number of iterations continues to increase, the accuracy of fault warning, response time of fault command, and amount of resources consumed generated by our method are generally superior to other methods. The maximum accuracy of fault warning is 99.82%, the minimum response time of fault instructions is 0.083 s, and the minimum amount of resources consumed is 118.57 MB, indicating that our method has a good power grid fault warning effect. Due to the inaccuracy of the method of Bai et al. [5] in dividing the risk threshold of power grid operation, the model may deviate in judging the fault state, thereby reducing the accuracy of fault warning. Meanwhile, this deviation may also affect the response time of fault command, making it difficult for the model to respond quickly after detecting a fault. The insufficient utilization of computational resources in the method of Gong et al. [6] may lead to performance degradation of the model when processing large amounts of data. This may result in a longer response time for the model during the fault warning process, while consuming more computing resources. This deficiency limits the efficiency and reliability of the model in practical applications.

From this, it can be seen that the method of this paper has strong understanding and analysis capabilities for the operation status of the power grid, high resource utilization, and can accurately distinguish between normal operation status and critical status before faults. At the same time, there is a good connection with the subsequent fault handling mechanism. After the fault command is output, it can quickly connect to the power grid system for early warning response, and the entire system can quickly respond to the warning.

4 Discussion

Based on the analysis of the above experimental results, it can be concluded that the method proposed in this paper has good performance in the fit between safety situation prediction results and actual values, safety situation discrimination, and fault warning, while the application effect of the two comparative methods is relatively inferior. Now use Table 6 to conduct a detailed analysis of the two comparison methods.

Table 6: Analysis of two comparative methods

Method	Specific process	Result	Limitations analysis
Method of Bai et al. [5]	A neural network model was constructed using radial basis functions to comprehensively process the operational data of the power grid system. Based on this, linear discriminant analysis was introduced into the model to establish an abnormal situation detection model for the power grid, which is used to perceive the trend of smart grid operation.	(a) The fit between the predicted results and the actual values is relatively low; (b) The accuracy of identifying the safety situation of smart grid operation is 89.32%, the recall rate is 90.01%, and the F1 score is 90.93%. In terms of numerical performance, it is inferior to the method of this paper; (c) The highest accuracy of fault warning is 91.38%, the minimum response time of fault command is 0.089 seconds, and the maximum amount of resources consumed can reach 155.28 MB. In terms of numerical performance, it is inferior to the method of this paper.	Although this method uses RBF to construct a neural network model and combines LDA to detect abnormal situations in the power grid, the RBF neural network has the problem of insufficient generalization ability when processing high-dimensional and complex data. LDA is difficult to fully capture the subtle changes in smart grid data in feature extraction and classification, which affects the perceptual accuracy of this method.
Method of Gong et al. [6]	By applying the cross entropy function and linear units, the loss evaluation part of the neural network model was optimized, and a fusion improved linear unit structure was constructed to achieve perception of the operation status of the smart grid.	(a) The fit between the predicted results and the actual values is relatively low; (b) The accuracy of identifying the safety situation of smart grid operation is 90.26%, the recall rate is 91.74%, and the F1 score is 92.18%. In terms of numerical performance, it is inferior to the method of this paper; (c) The highest accuracy of fault warning is 92.08%, the minimum response time of fault command is 0.098 s, and the maximum amount of resources consumed can reach 168.56 MB. In terms of numerical performance, it is inferior to the method of this paper.	Although this method optimizes the loss evaluation part of the neural network model through cross entropy function and linear unit, and constructs a model that integrates improved linear unit structure, it is still difficult to fully learn the intrinsic rules of the data when dealing with large-scale and high-dimensional data such as smart grids, resulting in prediction accuracy and reliability. Moreover, this method has shortcomings in terms of computational resource utilization, which limits the performance of the model when processing large-scale data and reduces the real-time performance of the method.

The method for this paper has adopted effective strategies to overcome the difficulties of situation awareness and fault warning in smart grids. Firstly, in response to the complexity and temporal nature of power grid data, a long short-term memory network model is adopted, which utilizes its powerful sequence data processing capabilities to effectively capture long-term dependencies in power grid data and improve the accuracy of situation prediction. Secondly, by constructing a smart grid digital twin situational awareness framework, comprehensive real-time monitoring of the power grid status has been achieved, providing a solid foundation for accurate early warning. In addition, the method for this paper also comprehensively considers the dynamic and static security of the power grid, selects indicators that comprehensively reflect the operation trajectory of the power grid, and further improves the accuracy of situational awareness and fault warning.

The innovative work of method for this paper is as follows: on the one hand, by combining digital twin technology and deep learning models, comprehensive mapping and real-time monitoring of the power grid status have been achieved, providing strong guarantees for the safe operation of the smart grid. On the other hand, by introducing LSTM networks, the shortcomings of traditional methods in processing time-series data have been effectively addressed, improving the accuracy and efficiency of situation prediction and fault warning. In addition, the method for this paper also proposes the principles and methods for selecting indicators for evaluating the situation of smart grids, providing new ideas for research in related fields.

In summary, the method for this paper has significant innovation and application value in the field of smart grid situational awareness and fault warning.

5 Conclusion

In summary, this article comprehensively introduces a smart grid situational awareness and fault warning method that combines deep learning technology. This method is based on the digital twin smart grid platform and constructs a smart grid digital twin situational awareness framework. By selecting situational evaluation indicators that can comprehensively reflect the dynamic and static security of the smart grid, real-time monitoring and prediction of the power grid status are achieved. The core lies in utilizing Long Short Term Memory (LSTM) networks for deep learning analysis of power grid data, effectively capturing long-term dependencies in the data, thereby accurately assessing the power grid safety situation and providing fault warnings. The experimental results show that this method exhibits high accuracy, high recall rate, and high F1 score in safety situation prediction, discrimination, and fault warning, with high accuracy of fault warning, short response time of fault command, and low amount of resources consumed. This article provides an efficient and reliable solution for the safe operation of smart grids, demonstrating the enormous potential and application value of deep learning technology in the field of smart grids.

In the next stage of work, we are considering exploring alternative deep learning architectures to achieve significant performance improvements in temporal data processing. At the same time, considering the scalability issues that current research may face when dealing with large-scale datasets, especially when dealing with test datasets exceeding 125 GB, efforts should be made to research and develop more efficient data processing algorithms and parallel computing technologies to alleviate potential limitations on computing resources and ensure smooth response to larger scale data challenges.

Funding

This work was supported by Henan Province Science and Technology Research Project: Research and application of machine learning in equipment fault diagnosis of smart grid (Grant: 242102240122).

References

[1] Zhang, M., Liu, Y., Cheng, Q., Li, H., Liao, D., & Li, H. (2024). Smart grid security based on blockchain and smart contract. Peer-to-Peer Networking and Applications, 17(4):2167-2184.

[2] Xia, Y., Zhang, X., Ge, H., Hao, S., & Zou, W. (2021). Optimal dispatching technology of distributed power generation based on situation awareness. American Journal of Electrical and Electronic Engineering, 9(1):7-11.

[3] Bondarenko, A. F., Govorun, M. N., & Satsuk, E. I. (2024). About the Brazilian power grid accident on August 15, 2023. Power Technology and Engineering, 58(3), 527-534.

[4] Presekal, A., Ştefanov, A., Rajkumar, V. S., & Palensky, P. (2023). Attack graph model for cyber-physical power systems using hybrid deep learning. IEEE Transactions on Smart Grid, 14(5), 4007-4020.

[5] Bai, J., Jiao, J., Han, M., Zhou, X., & Liu, C. Research on substation network security situational awareness strategy and equipment remote operation and maintenance. Applied Mathematics and Nonlinear Sciences, 9(1), 516-527.

[6] Gong, X., Wu, X., & Zhou, X. (2023). Deep learning-based security situational awareness and detection technology for power networks in the context of big data. Applied Mathematics and Nonlinear Sciences, 8(1), 2939-2956.

[7] Zhai, C., Nguyen, H. D., & Zong, X. (2022). Dynamic security assessment of small-signal stability for power grids using windowed online Gaussian process. IEEE Transactions on Automation Science and Engineering, 20(2), 1170-1179.

[8] Wang, P., Zhang, D., Gan, L., & Zhang, Y. (2024). Key technologies and applications of collaboration between digital power grid and Internet of Things. Digital Twins and Applications, 1(1):26-37.

[9] Han, J., Chen, Z., Hu, P., Li, H., Li, G., & Pi, T. (2023). Digital twin power grid oriented mobile edge network resource allocation model. IEEJ Transactions on Electrical and Electronic Engineering, 18(10):1682-1693.

[10] Steffen, A, & Tarik, R. (2023). Digital solutions for future grid complexity: The change in the grid forces the adoption of digital solutions to manage future complexity. Transformers Magazine, 10(SE2):44-47.

[11] Weng, L., Yang, L., Lei, Z., Huang, Z., & Chen, Y. (2024). Integrated bus voltage control method for DC

microgrids based on adaptive virtual inertia control. Journal of Power Electronics, 24(7):1163-1176.
[12] Geng, Q., Sun, H., Zhou, X., & Zhang, X. (2023). A storage-based fixed-time frequency synchronization method for improving transient stability and resilience of smart grid. IEEE Transactions on Smart Grid, 14(6), 4799-4815.
[13 Zhang, M., Liu, Y., Cheng, Q., Li, H., Liao, D., & Li, H. (2024). Smart grid security based on blockchain and smart contract. Peer-to-Peer Networking and Applications, 17(4):2167-2184.
[14] Li, Y., Ren, R., Huang, B., Wang, R., Sun, Q., Gao, D. W., & Zhang, H. (2022). Distributed hybrid-triggering-based secure dispatch approach for smart grid against DoS attacks. IEEE Transactions on Systems, Man, and Cybernetics: Systems, 53(6), 3574-3587.
[15] Hisham, M., Abdellah, B., Farag, A., & Kenan, B. (2024). Grid frequency stabilisation under magnitude and generation rate constraints. International Journal of Modelling, Identification and Control, 44(2):172-180.
[16] Sanju, K., Neeraj, K., & Prashant, S. (2024). Comparative performance study of different filtering techniques with LSTM for the prediction of power consumption in smart grid. IETE Journal of Research, 70(4):3646-3663.
[17] Yang, S., Yuan, A., & Yu, Z. (2022). A novel model based on CEEMDAN, IWOA, and LSTM for ultra-short-term wind power forecasting. Environmental Science and Pollution Research International, 30(5):11689-11705.
[18] Ngamroo, I., & Surinkaew, T. (2023). Control of distributed converter-based resources in a zero-inertia microgrid using robust deep learning neural network. IEEE Transactions on Smart Grid, 15(1), 49-66.
[19] Diaba, S. Y., & Elmusrati, M. (2023). Proposed algorithm for smart grid DDoS detection based on deep learning. Neural Networks, 159(1), 175-184.
[20] Zhang, X., Li, C., Xu, B., Pan, Z., & Yu, T. (2022). Dropout deep neural network assisted transfer learning for bi-objective Pareto AGC dispatch. IEEE Transactions on Power Systems, 38(2), 1432-1444.
[21] Rashmi, B., Matushree, K., Anamika, Y., & Mohammad, P. (2024). Load forecasting model using LSTM for Indian state load dispatch centre. Electrica, 24(3):601-615.
[22] Wang, Y., Liu, Y., Wang, M., Dinavahi, V., Liang, J., & Sun, Y. (2024). Resilient smart power grid synchronization estimation method for system resilience with partial missing measurements. CSEE Journal of Power and Energy Systems, 10(3):1307-1319.
[23] Attia, H., Takruri, M., & Al-Ataby, A. (2024). Intelligent algorithm-based maximum power point tracker for an off-grid photovoltaic-powered direct-current irrigation system. Clean Energy, 8(3), 48-61.
[24] Liang, H., Qian, C., Yu, W., Griffith, D., & Golmie, N. (2024). Assessing deep learning performance in power demand forecasting for smart grid. International Journal of Sensor Networks, 44(1), 36-48.
[25] Agrawal, A., Das, N., Jain, S. K., & Kulhar, K. S. (2024). LSTM controllers for power quality improvement in grid connected hybrid wind-pv-battery based power supply system. In E3S Web of Conferences. EDP Sciences. 540, 10007.
[26] Zhang, Z., Qin, B., Gao, X., & Ding, T. (2023). CNN-LSTM based power grid voltage stability emergency control coordination strategy. IET Generation, Transmission & Distribution, 17(16), 3559-3570.
[27] Hou, C., Xu, N., & Liu, S. (2025). Design of online monitoring method for distribution IoT devices based on DBSCAN optimization algorithm. Informatica, 49(5):181-194.
[28] Zhang, Y., Gao, Y., & Zhao, Z. (2025). Research on operation and anomaly detection of smart power grid based on information technology using CNN+Bidirectional LSTM. Informatica, 49(7):157-164.
[29] Huang, Q., Xian, H., Mei, L., Cheng, X., & Li, N. (2025). Intelligent distribution network operation and anomaly detection based on information technology. Informatica, 49(9):123-134.