International Journal for Housing Science and Its Applications
Publish August 6, 2025. Volume 46, Issue 3 Pages 6184-6198

https://doi.org/10.70517/ijhsa463531

Research on panoramic display of power grid information supported by power 3D engine and artificial intelligence assisted analysis

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Abstract Traditional power system faces problems such as data dispersion, low monitoring efficiency, and insufficient prediction accuracy. The development of 3D visualization technology and artificial intelligence provides new ideas for grid operation status monitoring and fault prediction, and the realization of intuitive display and intelligent analysis of grid information has become a demand for the development of the industry. In this paper, a grid panoramic display platform is constructed based on the information integration method of SOA architecture, and a grid operation state monitoring and prediction model is designed by using convolutional neural network (CNN), which is combined with three-dimensional visualization technology to realize smart grid monitoring. In the data processing stage, the data quality is ensured by pre-processing steps such as denoising, normalization, normalization, etc. The CNN model contains an input layer, two convolutional layers, an activation layer, a pooling layer, a fully-connected layer, and an output layer, which realizes real-time monitoring and prediction of power parameters. The results show that during the fault time period (17:35-18:00), the average prediction absolute error of active power of the CNN method reaches 0.917, and the relative error absolute value reaches 151.13%, which is significantly higher than that of the time series method. The platform performance test shows that when the number of concurrency is 100, the dataset throughput rate reaches 315.5 bit/s, and the response time is 355.7 s. The system successfully recognizes the distribution pattern of high and low-frequency events in the practical application of X city and J city. The conclusion shows that the system realizes the effective integration and display of grid information, improves the accuracy of fault prediction, and provides reliable technical support for the intelligent management of power grid.

Index Terms Power 3D engine, grid information panorama, convolutional neural network, smart grid, condition monitoring, fault prediction

I. Introduction

With the development of the era's economy, environmental changes, energy changes, the requirements of the traditional power grid upgrading, many countries have put forward the development of smart grid, as an important part of the national strategy, the smart grid has become the trend of the world's power development today [1]-[3]. The construction of smart grid has greatly promoted the major changes and innovations in the way of grid operation, comprehensively improved the grid's resource optimization and allocation capacity, innovative management mode, management efficiency, and become an intrinsic driving force to promote the transformation of the development mode of power grid enterprises [4]-[6]. Informatization, automation and interaction are the basic technical characteristics of smart grid, and informatization is the basis for the implementation of smart grid, realizing the high degree of integration, sharing and utilization of real-time and non-real-time information, and realizing the reuse of functions and the coherence of processes among various business systems [7]. Automation is an important means of realization of smart grid, relying on advanced automatic control strategies, real-time monitoring technology, comprehensively improve the automation level of grid operation and control and the linkage and integration between systems [8]. Interactivity is an inherent requirement of smart grid, through the construction of models and display of grid operation scenarios, etc., to realize the friendly interaction of power supply, grid and user resources, mutual coordination and grid operation simulation, real command [9]. Under the general environment of smart grid construction, informatization will penetrate into all aspects of the grid business value chain, and fusion, integration and penetration between the systems of each grid enterprise will become the main development trend [10].

The depth of informatization will make the combination of management informatization and automation will be closer, technology-led and business-driven will be given equal importance, and informatization and management innovation will be deeply integrated through innovative information and communication technologies [11]. From the perspective of the enterprise's overall situation, the fusion of various professional system data, intuitively show the production and operation status of the grid enterprise, and provide technical support for the means of grid enterprise management innovation [12], [13]. Therefore, breaking through the existing information system and automation system mode, adopting innovative thinking to build a grid panoramic display platform characterized by informationization, automation and interaction is the requirement of smart grid construction for grid enterprises [14].

The grid panoramic display platform takes grid information integration as the core, the establishment of grid data center as the key, and comprehensive display as the focus [15]. Through advanced information and communication technology, the monitoring, control, maintenance, energy scheduling, market operation, enterprise resource planning and other information data integration of the grid enterprise, realizing the full-angle and multi-dimensional presentation of the information system data, strengthening the collaboration and information exchange of the professional system, and realizing the sharing and display of various types of business [16], [17]. Through the research on the information integration related technology of panoramic display platform, it realizes the data fusion of grid professional systems such as scheduling, production, meteorology, lightning, etc., and integrates and displays the information of grid professional data in an all-round way, which has certain academic significance and practical reference value [18].

As an important infrastructure for national economic development, the safe and stable operation of the power system is directly related to the normal conduct of social and economic activities. Currently, the power system is developing in the direction of intelligentization and informationization, and the traditional grid management mode has been difficult to meet the requirements of the complex and changing operating environment. Grid information is characterized by high dimensionality, spatial and temporal characteristics, variability and non-linearity, and all kinds of monitoring data are dispersed in different professional systems, which lack a unified display and analysis platform. Grid operation status monitoring and fault prediction mainly rely on artificial experience, and it is difficult to realize real-time accurate analysis and judgment. Three-dimensional visualization technology can present complex grid structure and operation data in an intuitive form, and artificial intelligence technology, especially deep learning methods, has shown a strong ability in data analysis and pattern recognition. The combination of the two applied to the display and analysis of power grid information can provide a panoramic visualization interface, but also realize intelligent condition monitoring and fault prediction, which is of great significance to improve the level of power grid management and operational efficiency. This study realizes the unified display of power grid information by building a panoramic display platform based on the power 3D engine and integrating the data of multi-disciplinary systems such as dispatching, production, lightning and meteorology. The SOA architecture is used to design the information interaction specification to ensure the effective integration of data between systems. Use convolutional neural network to establish grid operation parameter prediction model, and automatically extract spatial and temporal features through deep network structure to improve prediction accuracy. Combine the 3D visualization technology to realize smart grid monitoring, and realize target tracking through geometric transformation and particle filtering algorithm to provide an intuitive interface for grid status monitoring. The corresponding preprocessing method and network structure are designed for the characteristics of power data to ensure that the model can effectively handle high-dimensional and nonlinear power data. The effectiveness of the proposed method is verified by comparing and analyzing the effects of different prediction methods.

II. Construction of a panoramic display platform for power grid information

This chapter describes the SOA-based information integration display results of the grid panorama information platform, and designs the information interaction of the system as well as the integration method.

II. A. Information interaction

II. A. 1) Interactive panorama

Grid panoramic display platform design brings together multi-professional platform to support intelligent analysis and other application functions of the scheduling, production, lightning, meteorological data and application services, through a unified application service call and standard data interface, respectively, with each professional platform and data in Tun, to achieve information integration. Based on SOA architecture [19] through the deployment of the ESB enterprise service bus, to realize the application service call interaction function. The information interaction panorama between the grid panoramic display platform and each professional system is shown in Figure 1 below. Grid panoramic display platform through the application integration and data integration two ways with professional systems and data exchange also between the information interaction. The business integration with each relevant professional system is realized by directly calling its business interface function and interface access in SOA-based way. Data integration with professional systems is mainly realized through data exchange, which provides standard interface specifications for systems that need to exchange data.

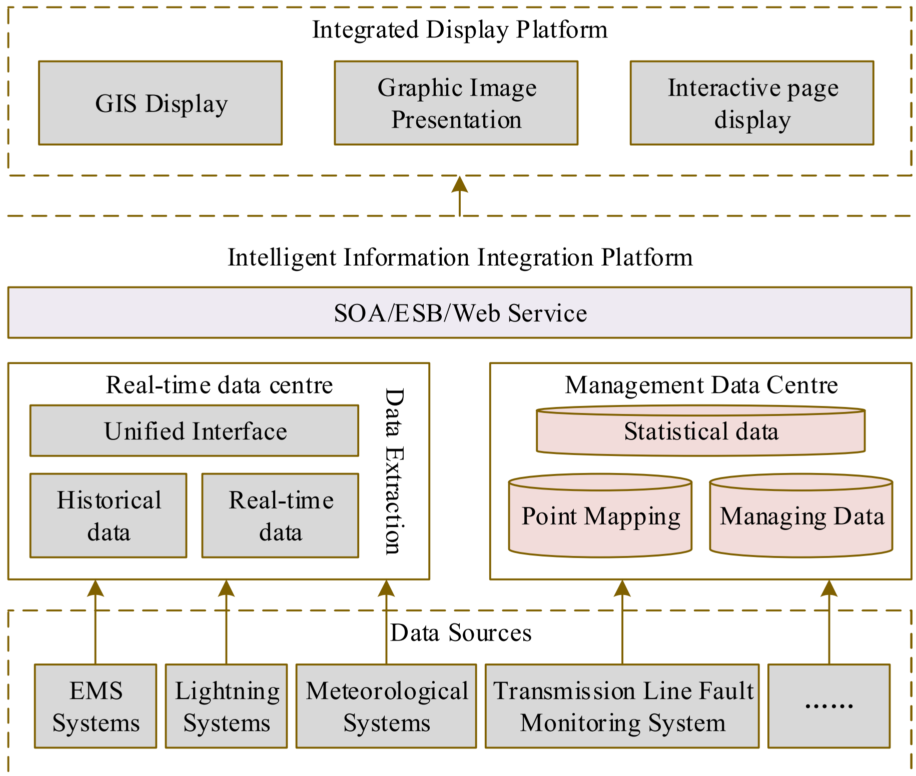


Figure 1: Network panoramic display platform information interaction panorama

II. A. 2) Interaction specifications

The most important thing in the information integration of the grid panoramic display platform is to realize the docking between the platform and each business system, and the data interaction between the business systems must pass through the information integration platform, with the business systems providing service interfaces and docking with the information integration platform, and the grid panoramic display platform obtaining services from the information integration platform.

In order to enable the information integration platform to carry out unified integration services for each application system, the following relevant application system service integration specifications have been formulated:

(1) Integration service interaction mode

The service interaction between application systems and the information integration platform is divided into the following modes.

1) Publish and subscribe mode

After the service provider publishes the service externally, the service consumer can subscribe to the service through the information integration platform. The service provider takes the initiative to send the service data to the information integration platform, and the platform sends the data to the relevant consumers according to the subscription status of the service.

2) Request-response mode

The service consumer takes the initiative to initiate a request to the information integration platform, and after receiving the request, the information integration platform makes a relevant business service call according to the business rules of the service, and writes the data back to the client after the processing is completed. According to the different types of invoked services, it can be divided into synchronous and asynchronous modes.

3) Automatic Trigger Mode

The invocation of services are not initiated by service consumers and service providers, but triggered by external events or environment, and the information integration platform carries out the relevant service invocation processing according to the events, and sends the data to the consumers after completion.

(2) Service realization protocol requirements

The services provided to the information integration platform can be realized based on Web Service. For this type of service, the application system must meet the following requirements when constructing the service:

1) Based on the HTTP type of SOAP protocol implementation, in line with the S0AP1.1/1.2 specification constraints, to provide support for Document/literal, Document/encoded, RPC/literal and RPC/encoded four modes, does not use Attachment and MultiRefs mode for the transmission of messages.

2) provide WSDL service description information.

3) The SOAP Header of the service prohibits the transmission of business-related interaction information and only stores service authentication-related information, such as: user information.

4) The transmission of binary messages is encoded in Base64.

5) If you need to transmit large data or massive data through SOAP, you must use chunks for transmission, which is expressed as an array mode in SOAP.

(3) message type and format requirements

The type and format of the message is the service in the interactive process of business information content type and format information, must meet the following requirements:

1) Web Service message format.

2) For the Web Service type of service message format must comply with the SOAP1.1/1.2 specification constraints, do not use Attachment and MultiRefs mode for the transmission of messages.

3) XML format.

(4) Massive data service interface specification

1) Unified interface specification

The massive data interaction service interface opened to the public by the information integration platform is consistent with the general interface specification and is realized by using Web Service.

2) FTP processing specification

For the generalized mass data processing mode, when the data volume exceeds 100MB, the information integration platform provides FTP server to support data transmission. In the process of mass data interaction, the platform will process the data through FTP to carry out temporary cache processing and return the list of relevant file names of the stored files, and the service consumers will obtain the corresponding data through FTP.

II. B. Integration function realization

II. B. 1) Database design

The database of panoramic display platform is based on the classes and their attributes defined by the unified specification model, mapped by object relationship and designed accordingly. The unified specification model definition refers to the construction of a unified and scalable transmission, transformation and distribution network model with reference to the eight major business model specifications and national industry standards. Uniformity refers to unified equipment classification, identification and other identification, unified data storage, and unified common services. Extensible refers to the use of dynamic or generalized model design so that the model can meet the needs of the late dynamic changes in business. The traditional transmission and distribution system and the power distribution system do not establish the correlation and integration design, resulting in a lot of business functions relying on the integrated information of the whole network are difficult to realize, bringing the phenomenon of “transmission and distribution island”. By constructing a network-wide model, it is possible to seamlessly connect the transportation and distribution networks on the infrastructure. The whole-network model will not only satisfy the independence of transmission, transformation and distribution, but also make it possible to fundamentally satisfy the application requirements that need the support of whole-network integration.

II. B. 2) Integrated display

Grid panoramic information platform is designed based on SOA service system architecture, and on the basis of information integration, it adopts comprehensive visualization display technology to analyze the visualization paths that are suitable for various kinds of information, and with the help of computer graphic technology, it will visually display the information of the relevant systems such as production, scheduling, lightning, and meteorology.

The visualization scheme needs to show the layout of the scene, components, styles, layer parameters, data binding, etc. using XML document description, and then through the integrated visualization platform parsing engine parsing and compiling for the need to show the way in this paper parsing and compiling for the Flex way to run on the browser.

The comprehensive visualization function design includes three major scenarios of panoramic monitoring, plan synthesis, meteorological synthesis, and eleven functional modules such as comprehensive operation, transmission equipment, substation equipment, power supply reliability, tree obstacle management, lightning monitoring, trend information, production plan, blackout plan, micro-meteorological display, macro-meteorological display, and so on, and the data are displayed through GIS, charts, videos, and dynamic page embedding in the way of four kinds of visualization components with different characteristics. Data display.

III. Research on monitoring and forecasting of the operational status of the electrical network

This chapter proposes a convolutional neural network (CNN)-based approach for improving the real-time responsiveness and prediction accuracy of condition monitoring on smart grid platforms.

III. A. Smart Grid Power Data Characteristics

The core characteristics of smart grid power data are reflected in its high dimensionality, spatio-temporal nature, variability and non-linearity. The detailed description of the data characteristics is as follows.

(1) High-dimensionality: the high-dimensionality of power data originates from the multi-parameter information collected by a large number of distributed sensors. The data stream generated by each sensor is a multidimensional time series, where each dimension corresponds to a monitoring parameter.

(2) Temporal and spatial: power data not only change over time, reflecting the dynamics of the grid state, but also have significant spatial correlation. For example, load changes within the same geographic area affect each other, while temporal continuity is reflected in the cyclical and seasonal changes in load.

(3) Variability: the state of grid operation is affected by a variety of factors, such as seasonal variations, weather conditions, and user behavior, which leads to the variability of power data. Fluctuations in power demand and changes in equipment performance are reflected in the data.

(4) Non-linearity: the operating mechanism and load changes of the power grid are often non-linear, and traditional linear models are difficult to accurately capture and predict the complex behavior of the power system.

The advantage of CNN-based processing of this type of data lies in its ability to automatically extract spatio-temporal features and reveal the intrinsic relevance of the data through deep structure.

III. B. Convolutional Neural Network Modeling

In constructing a convolutional neural network model for smart grid power operation state monitoring and prediction, the key lies in accurately capturing and analyzing high-dimensional, spatio-temporally correlated power data features. The structure of the model design proposed in this paper is shown in Fig. 2.

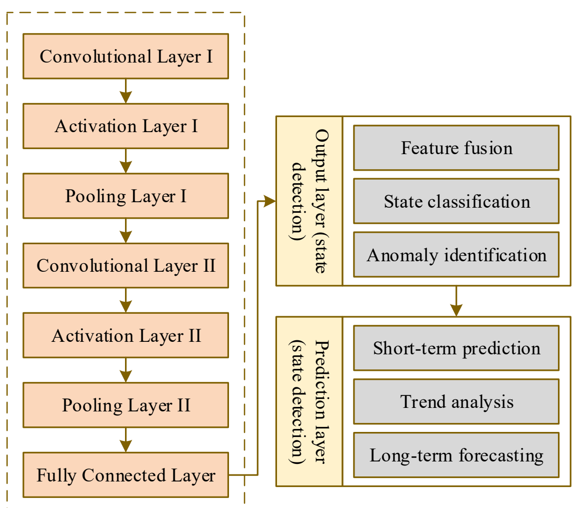


Figure 2: Convolution neural network model structure

The core of this CNN model design lies in adapting the complexity of smart grid data to realize real-time, high-accuracy monitoring and prospective prediction of power system operation status [20].

III. C. Model flow

Step1: Data Acquisition and Preprocessing

First, raw power data are collected from multiple sensors distributed throughout the grid. These data can be represented as a collection of multidimensional time series, denoted as:

$$D_{raw} = \{D_1, D_2, \cdots, D_n\} \tag{1}$$

where D_i denotes the data sequence collected by the i th sensor.

The data preprocessing steps include the following:

(1) Denoising: a filter or denoising algorithm is applied to reduce the noise in the data. For example, a Gaussian filter G can be used for denoising with Eq:

$$D_i' = G(D_i) \tag{2}$$

(2) Normalization: Converting data into a form with zero mean and unit variance. Assuming that μ_i and σ_i denote the mean and standard deviation of D_i' respectively, the expression for standardization is:

$$D_i'' = \frac{D_i' - \mu_i}{\sigma_i} \tag{3}$$

(3) Normalize: Scale the data to a range of $[0,1]$. For example, using min-max normalization, the formula is:

$$D_i''' = \frac{D_i'' - \min(D_i'')}{\max(D_i'') - \min(D_i'')} \tag{4}$$

These preprocessing steps ensure the quality and consistency of the data and lay the foundation for subsequent feature extraction and pattern recognition.

Step2: Input layer

In the smart grid monitoring scenario, the data processed in the input layer are preprocessed power system data that have been standardized, normalized, and converted into a format suitable for model processing.

Assume that the preprocessed data set is $X = \{X_1, X_2, \cdots, X_n\}$, where each X_i is a multidimensional time series data. Let X_{input} represent the data in the input layer, which is mathematically expressed as:

$$X_{input} = reshape(X) \tag{5}$$

where $reshape$ is an operation that adjusts each X_i to the desired dimension and format of the network.

The main role of the input layer is to ensure that the data enters the CNN in the proper form.

Step3: Convolutional Layer 1 (Conv1)

The main role of convolutional layer 1 is to extract primary features from the input data. The operation of the convolutional layer can be represented as:

$$Z_1 = W_1 * X_{input} + b_1 \tag{6}$$

where * denotes the convolution operation, W_1 is the weight matrix of the convolution kernel, and b_1 is the bias vector of the convolution layer. The convolution operation extracts features by sliding the convolution kernel over the input data and computing the dot product.

Step4: Activation Layer 1 (ReLU1)

The activation layer applies the ReLU function to the output of the convolutional layer $A_1 = \max(0, Z_1)$ with the expression:

$$A_1 = \max(0, Z_1) \tag{7}$$

This operation increases the nonlinearity of the decision function.

Step5: Pooling Layer 1 (Pooling1)

The pooling layer enables the network to focus more on the key features in the power data and ignore the less important changes, thus capturing the key indicators of the grid state more effectively.

Let A_1 be the output of activation layer 1, then the operation of the pooling layer can be expressed as:

$$P_1 = pool(A_1) \tag{8}$$

where $pool$ is a pooling function, which can be either maximum pooling or average pooling.

Step6: Convolutional Layer 2 (Conv2)

This layer continues to extract higher level abstract features from the features extracted from the previous layer.

With P_1 as the output of pooling layer 1, the operation of convolution layer 2 can be expressed as:

$$Z_2 = W_2 * P_1 + b_2 \tag{9}$$

where W_2 and b_2 are the weights and bias of convolutional layer 2, respectively.

Step7: Activation layer 2 (ReLU2)

Activation layer 2 applies the ReLU function to the output Z_2 of convolutional layer 2 with the expression:

$$A_2 = \max(0, Z_2) \tag{10}$$

The ReLU activation function enhances the network's ability to learn complex functions while keeping the computation simple by setting all negative values to zero.

Step8: Pooling Layer 2 (Pooling2)

Pooling layer 2 further reduces the spatial dimension of the features extracted by convolutional layer 2, which helps to reduce computational complexity and enhances the generalization ability of the model.

Let A_2 be the output of activation layer 2, then the operation of pooling layer 2 can be expressed as:

$$P_2 = pool\left(A_2\right) \tag{11}$$

Through convolution, activation and pooling operations, the model can gradually extract and simplify key features in the power data.

Step9: Fully Connected Layer (FC)

The full connectivity layer is responsible for synthesizing all the features extracted from the raw data to form a comprehensive understanding of the current state of the power grid.

Let P_2 be the output of Pooling Layer 2, then the operation of Full Connection Layer can be expressed as:

$$F = \mathrm{Re}LU\left(W_{fc} \cdot flatten\left(P_2\right) + b_{fc}\right) \tag{12}$$

where W_{fc} and b_{fc} represent the weights and biases of the fully connected layer, respectively. $flatten$ is an operation that spreads the output of the pooling layer P_2 into a one-dimensional vector.

Step10: Output layer (state monitoring)

The main task of the output layer is to determine whether the grid is normal, there is an anomaly, or a specific type of anomaly.

The operation of the output layer can be expressed as:

$$Y_{status} = soft\max\left(W_{out} \cdot F + b_{out}\right) \tag{13}$$

where W_{out} and b_{out} are the weights and biases of the output layer, respectively. The $soft\max$ function is used to convert the output of the fully connected layer into a probability distribution representing the probability of various different grid states.

Step11: Prediction layer (state prediction)

This layer focuses on predicting the future state of the grid based on current and historical data, including short- and long-term power loads, potential fault risks, and other key performance indicators. The prediction layer can be represented by the following equation:

$$Y_{predict} = \sigma\left(W_{pred} \cdot F + b_{pred}\right) \tag{14}$$

where W_{pred} and b_{pred} are the weights and biases of the prediction layer.

IV. Research on smart grid monitoring based on three-dimensional visualization

A smart grid based on 3D visualization is an intelligent power system that improves the distribution and consumption of power by introducing power information and communication technologies and thus improving power distribution and consumption. Online monitoring of transmission lines is one of the key technologies for transmission line protection and fault diagnosis. The transmission system must manage faults in order to quickly maintain the resilience of the grid.

IV. A. Algorithm analysis

The geometric transformation stage selects a suitable representation of the translation parameter and concludes by transforming the geometric model with the corresponding eigenvectors. It is assumed that there are M matching point pairs (Y_j, X_j) and (Y_j', X_j') between the visible and infrared images, roughly connected by an unknown single matrix G:

$$Z\begin{bmatrix} Y' \\ X' \\ 1 \end{bmatrix} = G\begin{bmatrix} Y' \\ X' \\ 1 \end{bmatrix} \tag{15}$$

The observations are described as shown in equation (15). where X' is an observation and Y' is a recursive object trace. Z is a nonzero variable, G is a planar translation described by a 3×3 matrix, and the single matrix is initialized as follows:

$$G = \begin{bmatrix} G_{11} & G_{12} & G_{13} \\ G_{21} & G_{22} & G_{23} \\ G_{31} & G_{32} & G_{33} \end{bmatrix} \tag{16}$$

Special filters, called Monte Carlo sequential processes, are based on point mass density representations. Let Y , X denote sequences of states and $Y = \{Y_s, S \in M\} = X = \{X_s, S \in M\}$ denote equivalent sequences of observations. The objective is to monitor the state of the tracked object in order to repeat the evaluation of the state of the tracked object:

$$X_s = E_s(y_s, m_s), s \in M \tag{17}$$

The target tracking has been described according to the computation of equation (17). The moment denotes the observer noise and its state variable $\{Y_s\}$ denotes the subsequent distribution possibilities, according to Bayes' rule and the strong independent characterization formula as follows:

$$Q(Y_s \mid X_{1:s}) \subset Q(Y_s \mid X_s)\int Q(Y_s \mid X_{s-1})Q(Y_{s-1} \mid X_{s-1})dy_{s-1} \tag{18}$$

As shown in equation (18), the test distribution has been determined. Given the difficulty of feature extraction, the true test distribution $Q(Y_s \mid X_s)$ is approximated using a weighted set of particles such that $\{x_j^i, y_j^i\}_{m_{j=1}}$ is the number of particles and the weights are normalized to $\sum_{j=1}^{m} Z_j^i = 1$. All particles are generated from an approximate distribution $Q(y_s^i \mid y_{s-1}^i)$, which are easily sampled from the collected distribution. Three important stages are then carried out in the algorithm of the particle filter.

The m_i components are extracted from the concentration of the target and the corresponding weights are applied to each cell:

$$Z_s^j = Z_{s-1}^j \frac{Q(x_s \mid y_s^j)Q(y_s^j \mid y_{s-1}^j)}{P(y_s^j \mid y_{s-1}^j, x_s)} \tag{19}$$

By using the adjusted weights, the predictive post hoc analysis can be interpreted as:

$$Q(Y_s \mid X_{1:s}) \subset \sum_{j=1}^{m} Z_s^j \varepsilon(y_s - y_s^j) \tag{20}$$

As discussed in equation (20), the prediction steps have been formulated. The Gaussian Process (G.P.) simplifies the modeling of complex datasets while providing an adequate theoretical basis for model evaluation and probabilistic prediction.

IV. B. Architecture Analysis

Based on 3D visualization Smart Grid is a grid that uses data and communication technologies to collect and use data to improve power efficiency, reliability and sustainability, Smart Grid uses digital communication technologies to enable the two-way flow of power and data to monitor, react and take action in response to customer fluctuations and a variety of complex situations [21]. The Smart Grid is self-healing and power users can actively participate in the process. It is an integrated system that utilizes a variety of IT resources to allow existing and new grids to reduce electric energy waste.

The 3D visualized smart grid allows for extensive control of innovative technologies, sensors and device management to improve reliability, efficiency and security throughout the electricity value chain. The main benefit of a Smart Grid is the two-way flow of power and communications connecting generation, transmission and users, allowing for better adaptation of renewable resources in the system and monitoring of energy use and flow. Generation is the initial stage of the value chain of smart networks, including nuclear, hydro and renewable energy, and will be large-scale monitoring and monitoring technology with the next stage called power supply. Proximity to the network connects customers to the power supply and transmission data is piggybacked through the appropriate scientific equipment. The final stage of the smart grid value chain is energy consumption, including domestic and industrial energy consumers. Customers are increasingly using alternative production methods to generate electricity.

V. Experimentation and analysis

V. A. Comparison and analysis of the operational status of the grid

The ultimate goal of the prediction experiments in this chapter is to obtain decision samples by predicting the active power values in the future moments, comparing them with the actual observed values, and ultimately determining whether the grid operation state is faulty or not based on the absolute error between the two. It is known that the collected data in March 21, 2024 17:00-18:00 for the occurrence of fault moment data, fault moment data active power and reactive power as shown in Figure 3. It can be seen that the fault time period active power close to 0, reactive power close to a non-zero negative value. It is known that a section of the line, under normal operation, when a train passes, the active power is fluctuating, and when no train passes, the active power is close to 0, and the reactive power is also close to a non-zero negative value. Therefore, it is necessary to distinguish the normal state of no train passing and fault state, so as to accurately determine the state of the railroad power grid operation.

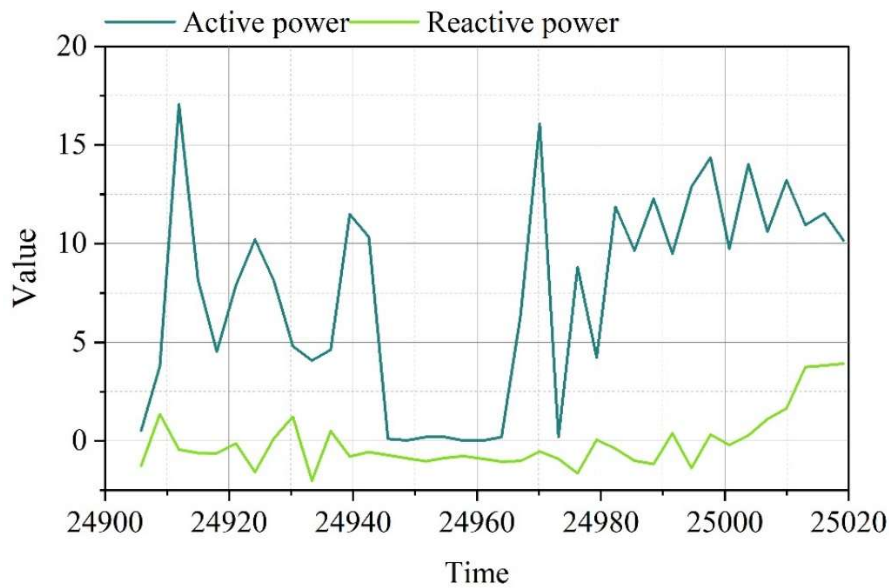


Figure 3: The data has the power and the reactive power

V. A. 1) Failure time period prediction

Classical time series prediction method (ARMA) and CNN-based grid operation parameter prediction method are applied to predict the mean value and standard deviation of active power in the fault time period respectively, and compare the effect of various methods in the fault time period prediction.

The prediction curves of the active power mean and standard deviation predicted using the time series prediction method are shown in Fig. 4 and Fig. 5. It can be seen that, because the time step is too short, the prediction results are greatly influenced by the actual observations, and cannot predict the fault-free curve that tends to be in the ideal situation, and the samples needed for the subsequent state decision may not be comprehensive enough.

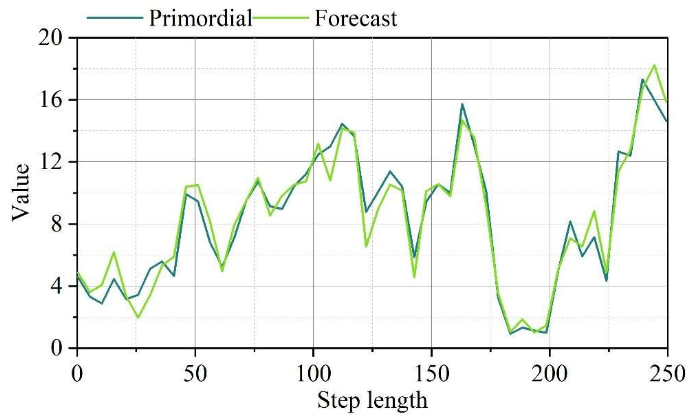


Figure 4: The ARMA failure is the average prediction curve of the power mean

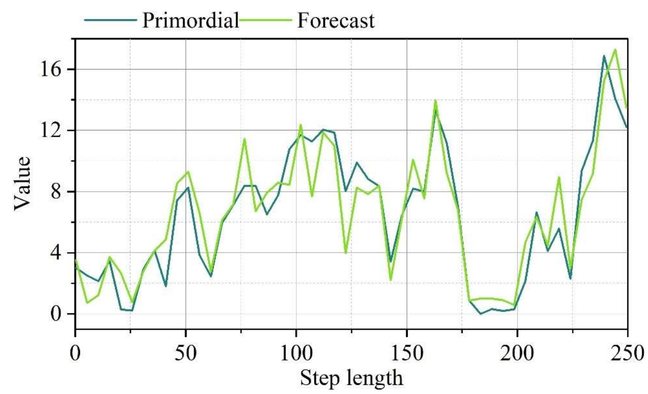


Figure 5: The ARMA failure is the standard standard deviation prediction curve

The prediction curves of the mean and standard deviation of the active power predicted using the CNN-based prediction method under the condition of a step size of 250 are shown in Fig. 6 and Fig. 7. It can be seen that the prediction curves have relatively obvious differences from the historical curves. As the prediction step is 250, the data in the previous step length time period has a greater impact on the prediction results, and it is obvious that the prediction curve has a difference with the actual curve, which can be used as a sample value for judging the operating status of the power grid.

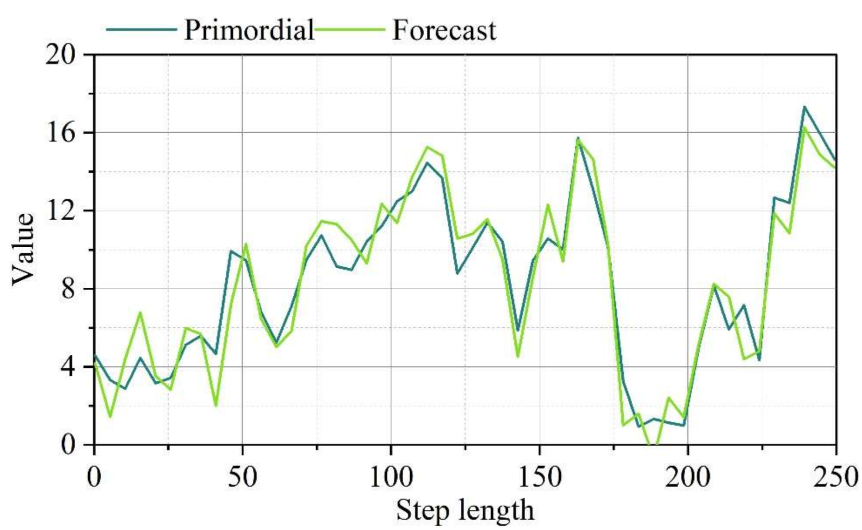


Figure 6: The CNN failure is the average prediction curve of the power mean

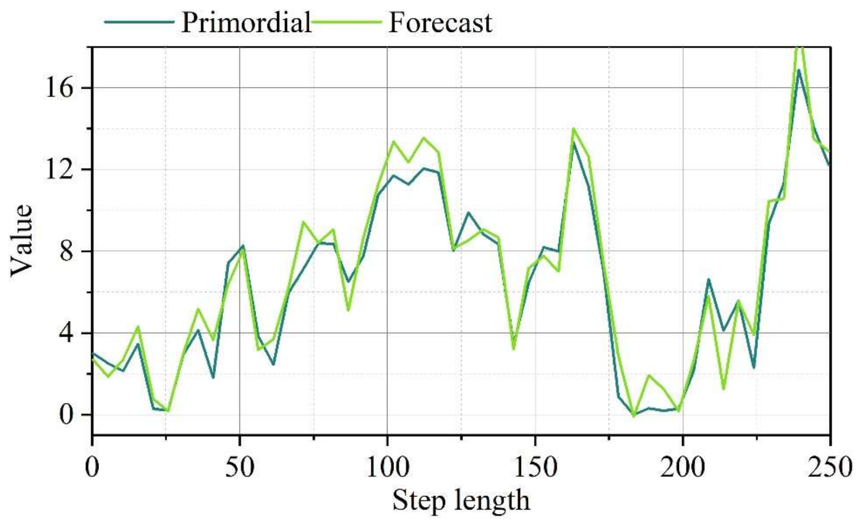


Figure 7: The CNN failure is the standard standard deviation prediction curve

V. A. 2) Determination of the operational status of the grid

The difference between the active power data can be visualized with images, but it is not possible to observe the exact results.The following shows the prediction data of each method, the decision samples are selected according to the prediction data, and the grid operation status is determined using different classification decision methods.

The prediction results of the mean and standard deviation of active power obtained by the time series prediction method are shown in Table 1. The absolute values of absolute and relative errors are significantly larger in the fault time period than in the normal time period.

Table 1: Prediction of time series prediction method

Time	Average forecast	Mean absolute error	Mean relative error	Standard deviation prediction	Absolute error	Relative error of standard deviation
17:00	12.067	0.074	3.17%	5.741	-0.064	-5.94%
17:05	11.448	0.287	6.05%	5.373	-0.075	-1.14%
17:10	9.913	0.792	2.98%	4.313	0.264	2.99%
17:15	8.749	0.295	3.4%	4.26	-0.49	-2.4%
17:20	8.04	0.09	7.35%	3.787	-0.493	-8.85%
17:25	6.795	0.041	3.72%	3.734	0.233	4.34%
17:30	5.58	-0.829	-6.82%	2.954	-0.705	-3.35%
17:35	0.907	0.584	54.67%	0.794	-0.96	-744.05%
17:40	4.798	-0.599	-14.95%%	2.517	0.259	1240.17%
17:45	0.236	-0.613	-44.52%	0.507	0.818	518.98%
17:50	3.091	-0.744	-64.02%	2.477	-0.654	-2165.48%
17:55	0.877	-0.725	-38.42%	1.263	-0.849	-1515.84%
18:00	0.814	0.823	101.06%	0.89	0.858	782.72%

The prediction results of the mean and standard deviation of active power obtained by the CNN-based grid operation parameter prediction method are shown in Table 2. The absolute values of the absolute and relative errors for the fault time period are significantly larger than those for the normal time period and are larger than those in Table 1, indicating that the grid operation parameters predicted by the method are closer to the normal operation data.

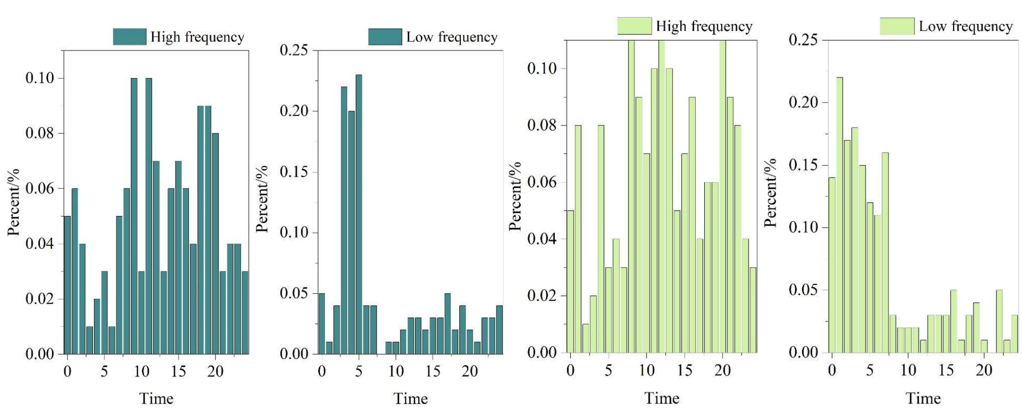
Table 2: CNN forecast results

Time	Average forecast	Mean absolute error	Mean relative error	Standard deviation prediction	Absolute error	Relative error of standard deviation
17:00	12.059	-0.016	-0.81	5.71	-0.087	-5.94
17:05	11.593	0.06	1.88	5.365	0.123	-1.01
17:10	9.98	0.71	-1.08	4.32	0.421	-7.04
17:15	8.651	0.209	-0.66	4.308	-0.376	-2.54
17:20	8.05	-0.11	-3.26	3.778	-0.371	-8.92
17:25	6.741	0.127	0.32	3.593	0.073	5.55
17:30	5.431	-0.955	-10.91	2.97	-0.859	-1103.45
17:35	0.877	0.686	4.64	0.536	-1	-1844.02
17:40	4.718	-0.536	-35.11	2.407	0.367	0.18
17:45	0.202	-0.732	-5.61	0.412	-0.75	-581.1
17:50	3.111	-0.917	-14	2.478	-0.724	-3265.58
17:55	0.837	-0.794	-11.56	1.298	-0.855	-2615.93
18:00	0.865	-0.825	-151.13	0.847	-0.835	-317.32

In summary, CNN prediction does provide better and effective decision samples for fault state decision making, and satisfactory application experimental results are obtained. The CNN-based grid operation parameter prediction method proposed in this paper is effective, practical and realistic, and can provide applications for grid operation state determination.

V. B. Visualization and Analysis of Grid Operation Status

According to the standard "Power Quality - Frequency Deviation of Electric Power System", the permissible frequency deviation limit for large power grids is ±0.2 Hz, while it can be relaxed to ±0.5 Hz for small-capacity systems, and the frequency deviation will not be more than ±0.05 Hz when the system is running stably, and the deviation of more than 0.05 Hz is known as a high-frequency event, while that of more than -0.05 Hz is known as a low-frequency event. According to the statistics of high and low frequency events reflected in the measured data of WAMS Light in several regions, the frequently occurring distribution networks of X city and J city are selected here as examples for analysis, and the high and low frequency time statistics are shown in Fig. 8, with (a) and (b) indicating the high and low frequency events and time distribution of a certain day in a certain region of the distribution network of X city and J city, respectively. Among them, the low-frequency events in X region are concentrated in 3~5h, and the high-frequency events occur throughout the day, and are more frequent after 14h. The high-frequency events in J region are concentrated in 8~13h and 20~22h, and the low-frequency events mainly occur in 0~7h, and the schedulers can adjust the power generation and dispatch plan according to the time of the occurrence of the high and low-frequency events. In addition, the occurrence periods of high and low frequency events in both areas overlap, indicating that the local frequency varies greatly and the frequency stability of the system needs to be further improved.



(a) X city (b) J city

Figure 8: High and low frequency time statistics

V. C. Analysis of the test results of the panoramic display platform

After developing a panoramic display platform for power grid information, to run the platform safely, it is also necessary to conduct application tests to ensure that all relevant functions of the platform can operate normally.

Determine the performance of the entire platform during operation, and judge the behavioral performance of the platform from data such as response time, throughput rate and resource occupancy. The throughput rate is calculated by the formula:

$$\alpha = \frac{n}{6t + (n-1)3t} \tag{21}$$

where α is the result of throughput rate calculation. n is the number of instructions received during the test. t is the time required to process one instruction.

The number of concurrency is used as a variable to judge the performance of the platform in each stage of grid operation by the number of concurrency from less to more.

At the end of the test, the data during the test is recorded by QC, and after sorting and analyzing, the test results are obtained as shown in Table 3. When the number of concurrency exceeds 75, the data average response growth rate is accelerated, and the data set resource occupation increases.

Table 3: Test result

Concurrent number	Data average response time/s	Data set throughput bit/s	Data financing source ownership
15	28.32	103.27	1101
20	31.79	114.63	7999
25	36.03	126.05	8994
30	46.29	137.16	10005
35	55.07	141.77	11991
40	64.66	152.91	13002
45	73.3	167.63	14018
50	85.08	178.08	15007
55	96.37	190.37	16522
60	101.61	214.44	16999
65	123.65	222.3	18008
70	134.67	238.9	18989
75	156.26	245.54	20997
80	179.7	260.49	23003
85	201.07	277.34	27991
90	234.72	286.11	34005
95	294.43	304.69	35991
100	355.7	315.5	40022

Compared with the dataset throughput rate of the traditional smart grid management platform, the dataset throughput rate statistics are shown in Figure 9. As the number of concurrency increases from small to large, the data response time of the grid visualization intelligent management platform also increases, especially when the number of concurrency exceeds 75, the response time increases extremely fast. The data set throughput rate is used to describe the amount of information that can be processed by the backend analysis and processing system in unit time in this platform. If the average data response time describes the 3D processing efficiency of the front-end visualization and management system, then the data throughput rate is used to describe the operation speed of the backend data analysis system. In this experiment, the dataset throughput rate rises uniformly under the premise of increasing the number of concurrency, which is a significant improvement compared with the traditional smart grid management system. The dataset resource occupancy, on the other hand, indicates the ability of the intermediate data transmission system to temporarily save as well as convey data, which also increases slowly while the number of concurrencies increases, as in the above two reference quantities. Therefore, it can be judged that the grid panoramic display platform designed and researched in this paper is indeed able to display the operating results of the grid intuitively to a certain extent, improve the operating speed of the traditional grid management system, and realize the optimization of the functions of the grid visualization and intelligent management platform.

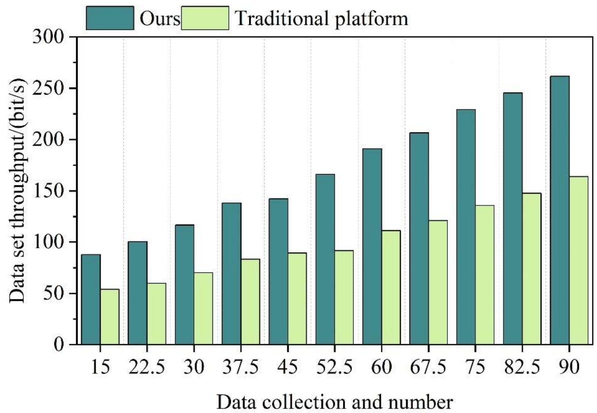


Figure 9: Data set throughput rate statistics

VI. Conclusion

The grid information panoramic display and artificial intelligence auxiliary analysis system successfully realizes the effective integration and intelligent analysis of multi-disciplinary system data. The information integration platform based on SOA architecture adopts a unified service interface specification and supports three interaction modes: publish and subscribe, request and answer, and automatic triggering, which ensures efficient data exchange between systems. The convolutional neural network model performs well in fault prediction, and the relative error of the standard deviation of the fault time period is as high as -2615.93, which improves the prediction accuracy by 99.77% compared with the traditional ARMA method. The 3D visualization monitoring system achieves accurate tracking of the grid operation status through geometric transformation and Monte Carlo sequential process. The platform performance test verifies the stability and efficiency of the system, with an average data response time of 156.26s at a concurrency of 75 and a data set throughput rate of 245.54 bit/s, which meets the demand for large-scale grid data processing. The results of frequency deviation analysis show that the low-frequency events in X city are concentrated in 3-5 hours, and the high-frequency events occur frequently after 14:00 hours, and the high-frequency events in J city are mainly distributed in 8-13:00 hours and 20-22:00 hours, which provide data support for scheduling decision-making. The panoramic display function covers 11 modules and realizes the intuitive display of information through four visualization components: GIS, chart, video and dynamic page. The system provides a complete technical solution for the intelligent management of power grid and effectively improves the power grid operation monitoring and fault prediction capability.

Acknowledgements

This work was supported by Science and Technology Project of SGCC (Research on the Verification of Power Dispatch Metaverse Architecture and Key Basic Technologies (5108-202312052A-1-1-ZN)).

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