EAI Endorsed Transactions
on Energy Web
Research Article EAI.EU

Large Model-Driven Task Generation and Multidimensional Verification for Power Grid Operation

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Abstract

INTRODUCTION: The generation technology of power grid operation tasks is crucial for ensuring the stable operation of the power system, and the accuracy and safety of task generation are even more critical. Traditional task generation methods are difficult to fully consider various factors such as grid load and reactive power, and suffer from poor adaptability and limited optimization capabilities.
OBJECTIVES: The research aims to solve the bottleneck problems of traditional methods in inaccurate power grid state judgment, lagging rule updates, difficult data fusion, and low verification efficiency, and provide efficient decision support for operation and maintenance personnel in complex power grid regulation scenarios.
METHODS: A hybrid approach combining rule engines and large model drivers is proposed. First, a power grid business rule library is constructed based on a rule engine, separating business rules from code to achieve fast matching and evaluation of real-time voltage, current, and other data; Then, using a large model to learn historical operational data and actual experience, predict the power grid status and generate multiple decision options; Finally, edge computing algorithm is introduced to process and schedule real-time data locally, reducing bandwidth pressure and improving response speed.
RESULTS: When the research method was iterated 82 times, the recognition accuracy was 94.35%, and the recognition accuracy increased with the increase of iteration times. Additionally, empirical analysis of the proposed intelligent generation technology for power grid operation tasks revealed that when tested on node 1, the operation response time was 8.2ms, the transmission rate was 22.1Mbit/s, and the overall operation response speed was fast.
CONCLUSION: The research method can effectively improve the feature recognition accuracy and task generation efficiency of power grid data, significantly reduce operational risks, and has high practicality and reliability.

Keywords: Large model-driven, Power grid operation task generation, Multidimensional verification, Edge computing, Rule engine

Received on 02 February 2026, accepted on 25 May 2026, published on 09 June 2026

doi: 10.4108/ew.11803

1. Introduction

With the rapid development of the social economy, the scale of modern power grids continues to expand, leading to increasingly complex structures and rapidly changing operating conditions [1]. Power grid operation tasks are essential for ensuring the stability of power systems, and the accuracy and security of task generation are critical. Traditional task generation methods struggle to fully consider factors such as grid load and reactive power, resulting in limitations in adaptability and optimization [2-3]. Li et al. and Naderi et al. proposed an artificial intelligence based operation method for renewable energy generation systems to

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address issues such as weak power dispatch. The results indicated that this method could meet the requirements for power system prediction, scheduling, and control [4-5]. Additionally, multidimensional verification plays a key role in ensuring task feasibility and safety by automatically verifying parameters such as electrical quantities. However, traditional verification methods have poor integration efficiency for data from substations and transmission lines. In response, Lin et al. proposed a robot vision-based self-verification algorithm to improve substation verification accuracy. The results show that this algorithm preserves more correct matching points during the feature matching stage [6]. Based on the above content, it can be concluded that the existing research on generating power grid operation tasks mainly falls into three categories. Rule-based methods rely on expert-defined thresholds; although these methods possess strong interpretability, they struggle to cover atypical operating conditions. Rule updates lag behind changes in the power grid [7]. Traditional machine learning methods can learn discriminative boundaries from data, but the model capacity is limited and it is difficult to capture the long-range dependencies and nonlinear coupling characteristics in power grid time-series data [8]. Furthermore, model outputs often lack interpretability and are not effectively integrated with grid safety rules. Consequently, a significant gap exists regarding the closed-loop feedback mechanism between multidimensional verification technology and generative models [9-10]. Therefore, the technology proposed in this study, which combines large model driven and multi-dimensional verification, compensates for the shortcomings of existing methods in task generation integrity, security constraint compliance, and generation verification closed-loop mechanism through a serial architecture of rule engine pre filtering, large model core generation, and multi-dimensional verification post verification. The large model is a deep learning model with large-scale parameters, which utilizes historical power grid operation data and scheduling records for pre-training. The model is capable of learning inherent laws and spatiotemporal evolution patterns of power grid operation, and generate executable operation tasks based on them. The main innovative contributions of the research are reflected in the following three aspects. First, unlike existing research that relies solely on rule engines for simple threshold judgments, this study deeply integrates rule engines with multidimensional verification techniques to construct a power grid business rule library that covers four types of rules: electrical quantities, equipment status, topology, and safety and stability. This achieves complete separation between business rules and execution code, thereby improving the flexibility and maintainability of real-time data matching and evaluation in complex power grid scenarios. Second, distinguished from existing literature that attempts to apply large models solely to load forecasting or fault diagnosis, this study proposes a task generation framework driven by the large model and edge computing algorithm. The large model is responsible for learning the deep semantic characteristics and spatio-temporal evolution laws of power grid operation from historical data, and the edge computing algorithm completes real-time processing and rapid response at the data source. The collaboration between these two components effectively resolves the inherent contradiction between global modeling and local real-time processing in traditional methods. Thirdly, a three-stage closed-loop task generation process of "rule engine pre verification large model generation multi-dimensional verification post verification" has been developed. This process uses the rule engine for feasibility screening before generating operational tasks, and uses multi-dimensional verification technology for four-dimensional joint verification of electrical quantities, safety and stability, topology structure, and operational rules after generation, thereby achieving dual risk control throughout the entire task generation chain. This technology is expected to overcome the limitations of traditional methods, accurately generate power grid operation tasks, and comprehensively verify data.

2. Optimization of power grid operation task generation and multidimensional verification technology combining multiple methods

2.1. Multidimensional verification of power grid data based on rule engine

The power system is large and complex; thus, the transmission, management, and distribution of electrical energy data are critical factors for stable operation. However, massive power data flowing through the network may lead to data leakage and difficulty in identifying abnormal data, a challenge that traditional power grid data processing methods cannot effectively address. To solve the issues of difficult data assessment and feature extraction in power grids, this study introduces a multidimensional verification method based on a rule engine to enhance data processing capabilities and security performance. The rule engine separates business rules from code, improving system flexibility and maintainability while enabling rapid processing of large amounts of real-time data for efficient matching and decision-making [11-12]. The specific process of using a rule engine for power grid data processing is shown in Figure 1.

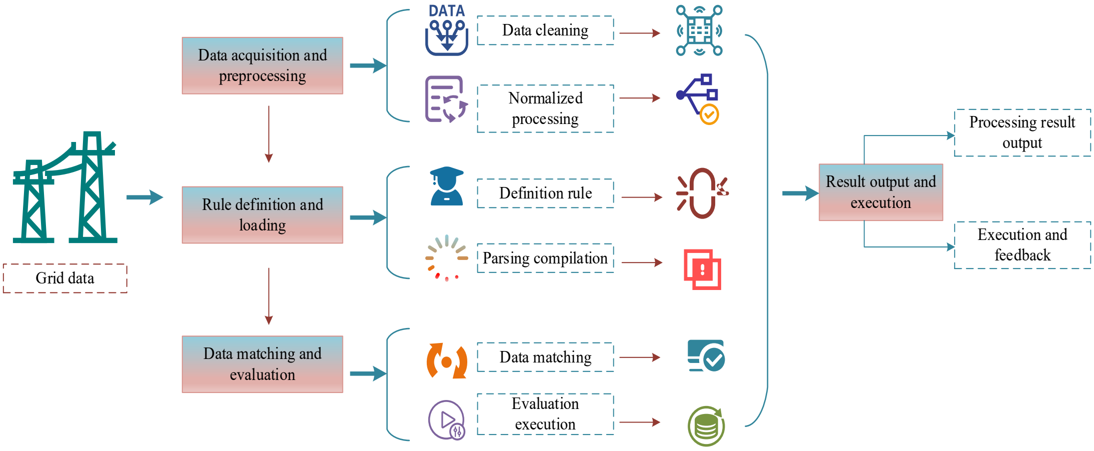


Figure 1. Detailed flow chart of using rule engine to process power grid data

As shown in Figure 1, the rule engine-based power grid data processing method consists of four parts: data collection and preprocessing, rule definition and loading, data matching and evaluation, and result output and execution. First, the data collection process gathers real-time operational data from relevant sensors and cleans or corrects the data. Then, domain experts define power grid data constraints and judgment rules, refining classification for different application scenarios. Next, the processed data is matched with the parsed and loaded rules to determine whether voltage, power, and other data comply with power grid operation requirements. Finally, the rule engine outputs and executes the processing results, presenting them visually to relevant personnel. To further enhance data processing capabilities, the proposed method integrates multidimensional verification technology to optimize grid regulation. Multidimensional verification technology fuses various data types such as electrical quantities and equipment status and performs automatic verification under different operating conditions. The improved average clustering calculation for power grid information is shown in Equation (1).

$$S_t = \frac{1}{N}\sum_{x=1}^{k} S(x). \tag{1}$$

In Equation (1), x represents the power grid data set, k represents data information, and $S(x)$ represents the probability of abnormal power grid data. The calculation for highly threatening abnormal power data is shown in Equation (2).

$$S_t = \sum_{x=1}^{A} P_x \times S_x. \tag{2}$$

In Equation (2), x represents power grid abnormal faults, P_x represents the frequency of fault occurrences, S_x represents the degree of harm, and A represents the number of accidents caused by predicted faults. The multidimensional channel attention mechanism for power grid data is shown in Equation (3).

$$M_c(F) = Soft\max\left(W_1\left(W_0\left(F_{avg}^{c}\right)\right) + W_1\left(W_0\left(F_{\max}^{c}\right)\right)\right). \tag{3}$$

In Equation (3), F represents power grid data features, F_{avg}^{c} represents descriptors after average pooling, $F_{\max}^{c}$ represents descriptors after max pooling, and $W_0 \in \mathbb{R}^{C/r\times C}$ and $W_1 \in \mathbb{R}^{C\times C/r}$ are parameters. The regional scheduling range adjustment for power grids is shown in Equation (4).

$$\bar{R} = (1/N)\times\sum_{R=1}^{N} R_i. \tag{4}$$

In Equation (4), $\bar{R}$ represents the adjusted regional scheduling range, N represents the number of different types of distribution network nodes, and i represents the number of power grid scheduling data features. In summary, the rule engine and multidimensional verification can process real-time voltage and current data in a timely manner to ensure stable power grid operation. The structural framework of the multidimensional verification-based power grid data processing method is shown in Figure 2.

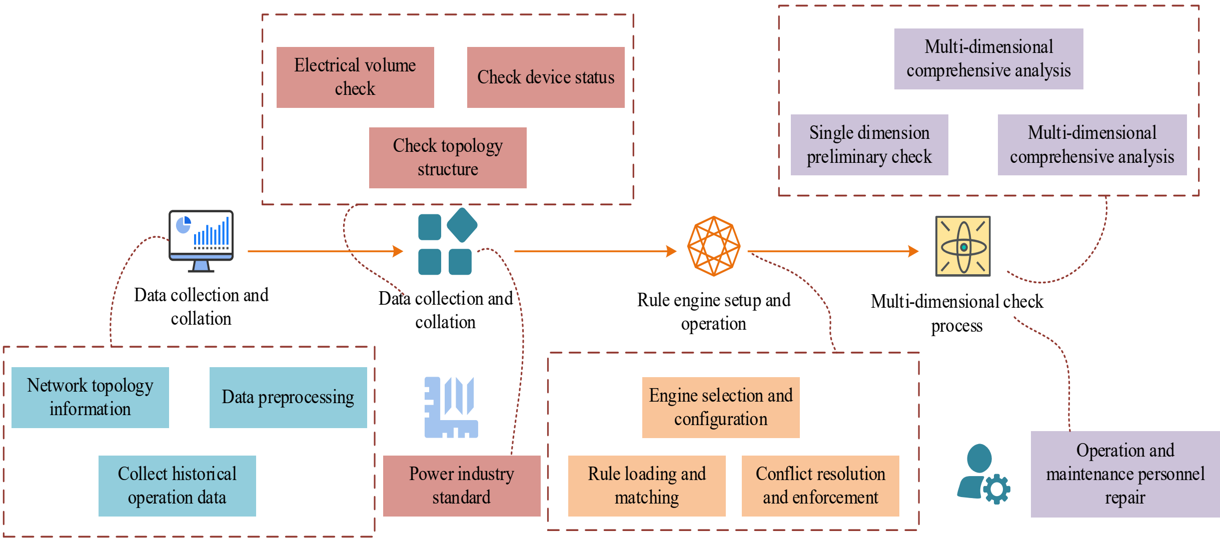


Figure 2. Power grid data processing method based on rule engine

As shown in Figure 2, the structural framework of the multidimensional verification-based power grid data processing method mainly includes four parts: data processing and organization, rule definition and classification, rule engine construction and execution, and the multidimensional verification process. First, power grid topology information and historical operational data are collected and preprocessed. Then, power grid operation rules are formulated based on industry standards, and verification rules are classified into three types: electrical quantity, equipment status, and topology structure. Next, a rule engine suitable for handling complex power system rules is selected, and rule execution priorities are set. The defined rules are then loaded into the rule engine and compiled into efficient execution code, where rule conditions are matched with data. Finally, verification is conducted on both single-dimensional and multidimensional levels, and the results are integrated and fed back to grid dispatching and operation teams to determine potential faults. The dynamic scale binary deterministic calculation for power grid data is shown in Equation (5).

$$I^{t+1} = \begin{cases} I^c, r_s^t \le \tau \\ I, or \end{cases} \tag{5}$$

In Equation (5), τ represents the decision threshold for controlling power grid data, I^{t+1} represents a small batch of input network data, I^c represents the current time-series data for future iterations, and r_s^t represents the loss ratio. The probability of power grid data undergoing self-verification and scheduling through grid nodes is shown in Equation (6).

$$\Omega_{ij}(t+1) = s_i(t)\omega_{ij} \tag{6}$$

In Equation (6), i represents power grid data nodes, j represents different information node numbers within a grid region, and t represents a specific moment in time. In summary, the multidimensional verification-based power grid data processing method can efficiently schedule power grid information and conduct self-verification for fault data.

2.2. Large model-driven task generation technology with multidimensional verification

Although the multidimensional verification-based power grid data processing method can regulate power grid information, it still has limitations in power grid operation task generation. To address issues such as inaccurate power grid state judgment and delayed rule updates, this study proposes a power grid operation task generation technique driven by a large model to improve the efficiency of extracting key information for dispatchers. The large model learns from extensive historical data and real-world operational experience to accurately predict power grid responses under different conditions [13-15]. Additionally, it continuously adjusts its structure and parameters to adapt to grid development changes [16]. The improved power grid data management framework using a large model is shown in Figure 3.

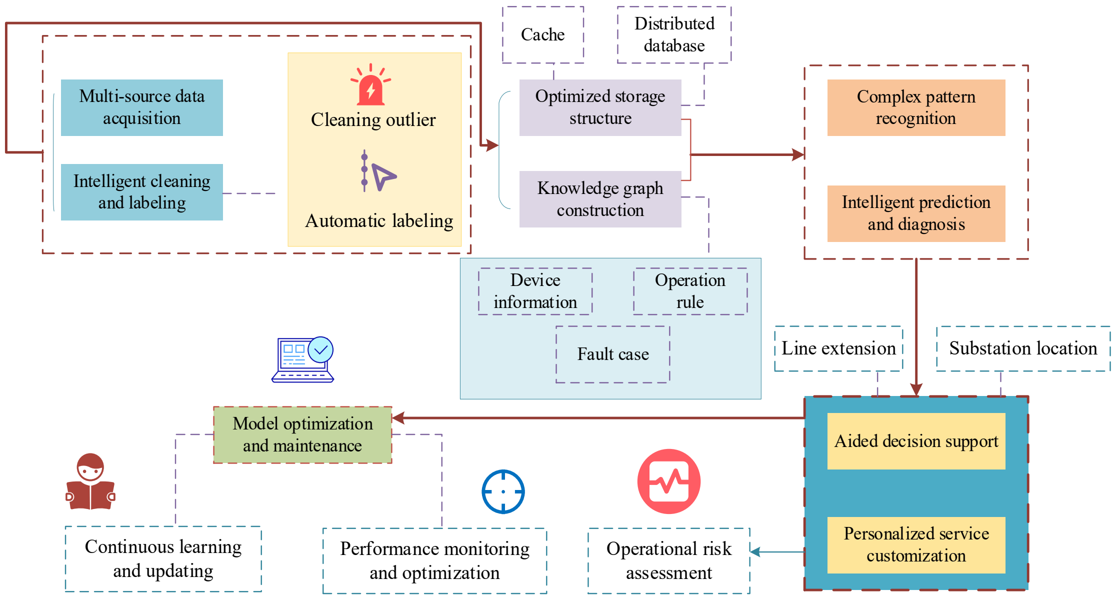


Figure 3. Improved power grid data management method driven by large models

As shown in Figure 3, the large model-driven power grid data management method first collects various data, such as voltage and current, and then cleans and identifies anomalies, automatically labeling parameters related to operating conditions and equipment. The model then optimizes the real-time data storage structure and constructs a power grid knowledge graph for convenient query and inference. To further analyze data, the large model identifies complex grid patterns and predicts future voltage levels and equipment failures. It then generates multiple decision options, providing solutions for line expansion and substation site selection to aid decision-makers. Finally, the model continuously learns and updates with new grid data, monitoring prediction accuracy and computational performance in real time. Although large model-driven techniques effectively manage grid data, inaccuracies may still occur in operation task generation. Therefore, this study integrates edge computing algorithms with large model-driven techniques to reduce operational risks in power systems. Edge computing reduces network bandwidth usage and enhances data security [17-19]. The power grid knowledge graph constructed in the study adopts a top-down construction strategy, first defining the ontology pattern layer, and then extracting entities and relationship instances from structured and unstructured power grid data based on this pattern layer. The ontology pattern layer is designed based on standard power grid specifications, comprising four core entity types: equipment, measurement, topology, and operations. The equipment category includes primary equipment such as generators, transformers, transmission lines, busbars, circuit breakers, isolating switches, as well as secondary equipment such as protection devices and measurement and control devices; Measurement categories include electrical measurement entities such as voltage, current, active power, reactive power, and phase angle; Topology classes include topological entities such as nodes, branches, and plants; The operation category covers business entities such as operation tasks, operation instructions, and operation tickets. The types of relationships between entities include physical connection relationships, electrical measurement relationships, topological inclusion relationships, operation execution relationships, and temporal dependency relationships, each of which defines clear domain and value domain constraints. The above ontology pattern is formally expressed in the form of a resource description framework triplet, where each knowledge representation is a "subject predicate object" structure, where the subject and object correspond to entity nodes, and the predicate corresponds to relationship edges.

In terms of knowledge representation learning, the TransE model is used for graph embedding, mapping entities and relationships in the knowledge graph to the same low dimensional continuous vector space. The TransE model is based on the translation assumption, which means that for each correct triplet, the sum of the head entity vector and the relation vector should be approximately equal to the tail entity vector. Model training employs a negative sampling strategy, where negative examples are generated by randomly sampling erroneous triplets that do not exist in the knowledge graph. The loss function uses interval based ranking loss to distinguish between positive and negative examples. After training, each power grid entity is represented as a low dimensional vector with a dimension of one hundred, and each relationship is also represented in vector form. Based on the graph embedding representation obtained from learning, the model can calculate the semantic similarity between different entities, infer implicit entity associations, and support semantic retrieval and inference operations based on vector distance. The sequence of power grid operation results established by edge computing is shown in Equation (7).

$$y = \gamma_0 + \gamma_1 x_1 + \gamma_2 x_2 + \ldots + \gamma_p x_p + \varepsilon \tag{7}$$

In Equation (7), y represents the predicted results for photovoltaic generation, charging stations, and load, while γ and $x_1, x_2, \ldots, x_p$ are the prediction estimation and influence factor coefficients, respectively. ε represents the error term in the prediction process. The operation task classification calculation is shown in Equation (8).

$$L\left(y_i, f\left(x_i\right)\right) = \sum_{i=1}^{n} L\left(y_i, f\left(x_i\right)\right) + \lambda \sum_{k=1}^{k} f\left(k\right) \quad (8)$$

In Equation (8), L and k represent the loss function for measuring prediction error and the number of model iterations, respectively, while n and λ represent the number of training samples and the regularization term weight, respectively. The evaluation of the operational efficiency value for the improved power grid operation task generation technique is shown in Equation (9).

$$S_2' = \sum_{i=1}^{n} C(D_i) \quad (9)$$

In Equation (9), $C\left(D_i\right)$ represents the effective coefficient of power grid equipment operation, D_i represents equipment, and n and i represent the day and time period index, respectively. The structural efficiency improvement of optimized regional power grid topology is shown in Equation (10).

$$\begin{aligned} V_l^{(t+1)} &= w \times V_l^t + c_1 \times r_1 \times \left(p_l - x_l^t\right) \\ &+ c_2 \times r_2 \times \left(g - x_l^t\right) \end{aligned} \quad (10)$$

In Equation (10), c_1 and c_2 represent learning factors, p_l represents the best individual position in the power grid data, g and V_l^t represent the global best position and current position, and w and $V_l^{(t+1)}$ represent inertia weight and next-generation velocity, respectively. The scheduling operation risk calculation in the improved power grid operation task generation technique is shown in Equation (11).

$$R_x = h\left(R_{0,x}\right) = \begin{cases} R_{0,x} & 0 \le R_{0,x} < 1.5 \\ 1.1R_{0,x} & 1.5 \le R_{0,x} < 2.0 \\ 1.2R_{0,x} & R_{0,x} \ge 2.0 \end{cases} \quad (11)$$

In Equation (11), x and R_x represent operation and operational risk, while $R_{0,x}$ and $h\left(R_{0,x}\right)$ denote the initial computation risk and the introduced function, respectively. The original operational risk calculation for the improved power grid operation task generation technology is shown in Equation (12).

$$R_0(x) = P_x \sum S(x_i) \quad (12)$$

In Equation (12), $R_0\left(x\right)$ represents the failure probability of an operation task, $S\left(x_i\right)$ denotes the operation value, and i refers to a specific operation within the operation task. The calculation of dispatcher failure rate for the improved power grid operation task generation technology is shown in Equation (13).

$$\lambda_p = exp\left[-\left(\frac{t}{T_{0.5\alpha}}\right)^{\beta}\right] \quad (13)$$

In Equation (13), t and $T_{0.5\alpha}$ indicate the response time and the intermediate time required for the scheduling source to complete a specific grid operation, respectively. α represents the scale of the cognitive behavior model, while β denotes the shape factor. In summary, the power grid operation system generation technology, driven by large models and edge computing algorithms, effectively assists dispatchers in managing grid risks and enhancing operational task safety [20]. The specific framework of the power grid operation task generation technology, driven by large models and multidimensional verification, is shown in Figure 4.

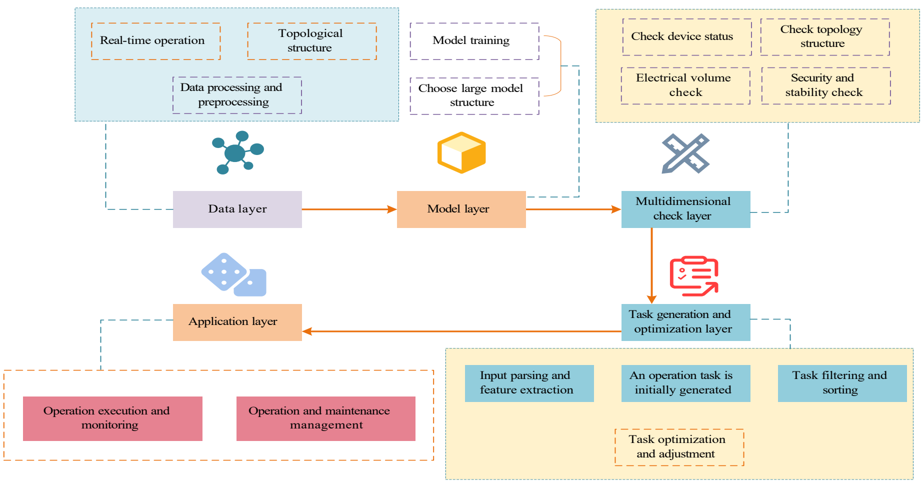


Figure 4. Grid operation task generation technology framework

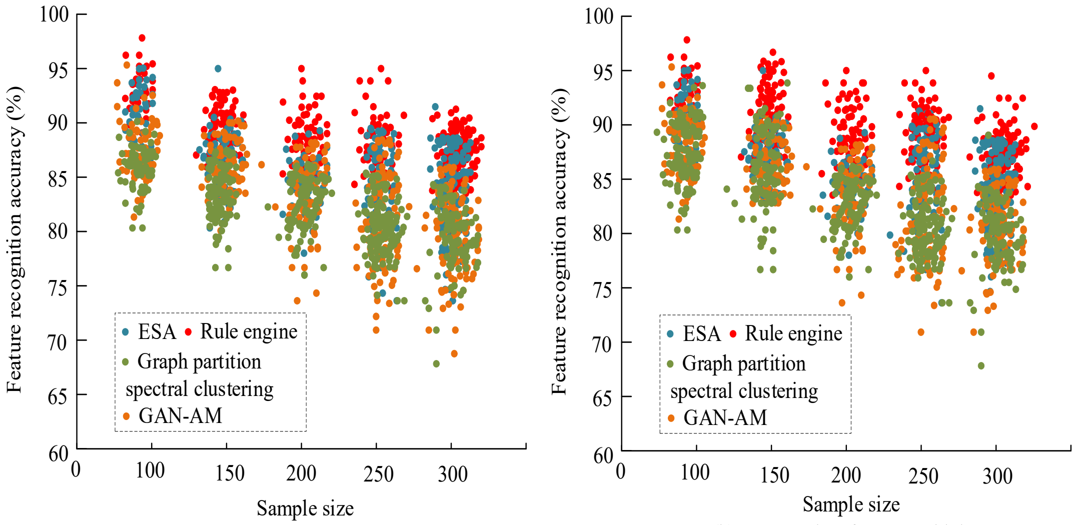
As shown in Figure 4, the power grid operation task generation technology, driven by large models and multidimensional verification, requires collecting fundamental data such as topology structures and historical operation records at the data layer. The collected raw data undergoes cleaning and noise reduction. At the model layer, an appropriate large model architecture is selected to process complex data structures and semantic information. The chosen model must also be regularly updated and optimized. In the multidimensional verification layer, verification is performed on electrical quantities, security stability, operational rules, and topology structures to ensure the stable operation of the power grid. During verification, a rule engine is utilized to promptly schedule power grid data, enhancing the system's data management capabilities. The trained model is then refined and adjusted to generate high-quality operation tasks. The optimized operation tasks are delivered to dispatch personnel or automated control systems for execution. Among them, the large model and rule engine in the research adopt a technology integration architecture that combines serial coupling and feedback verification. Specifically, the rule engine plays a dual role as a pre filter and post validator in the system, while the large model serves as the core decision generator. In terms of data flow, real-time collected grid voltage, current, power, and equipment status data first enter the rule engine. The rule engine quickly matches and verifies the legality of the input data based on predefined electrical quantity constraint rules, equipment status mutual exclusion rules, and topology connectivity rules. Only data that has passed the pre validation of the rule engine will be sent to the input layer of the large model. Data that has not passed the validation will be directly marked as abnormal and trigger an alarm, and will not enter the subsequent task generation process. After generating candidate operation tasks in the large model, the task is output to the validation interface of the rule engine in the form of a structured instruction sequence. The rule engine now starts the multidimensional verification module, which verifies candidate tasks item by item from four dimensions: electrical safety, equipment compatibility, topology integrity, and compliance with operating rules. Each dimension corresponds to a set of executable rules, and the rule engine pattern matches task instructions with rule conditions and calculates a matching score. When the matching score of a candidate task exceeds the preset threshold in all four dimensions, the task is judged as passing the verification and sent to the execution stage; If any dimension fails the validation, the rule engine will send the specific rule conditions that did not pass as feedback signals back to the large model. The large model will adjust its generation strategy accordingly and avoid violating rule constraints in the next round of generation, forming a closed-loop iterative mechanism of "generation validation feedback regeneration". The business rules defined in the rule engine adopt a separated storage structure, independent of code maintenance in JSON format. The large model does not directly access the underlying implementation of the rule library during training or inference during training and inference, but calls the rule matching results through the application programming interface provided by the rule engine, thereby decoupling rule updates from the retraining of the large model. This enables the adjustment of power grid business rules to take effect without retraining the large model. The above integrated architecture ensures that the deterministic constraints of the rule engine and the learning and generation capabilities of the large model complement each other technically, rather than interfering with each other.

In addition, the training process of large models is divided into two stages: pre training and fine-tuning. The pre training stage adopts a self supervised learning approach, where the model takes massive historical operation data of the power grid as input. Through masked prediction tasks, the model is trained to make predictions based on context, learning the spatiotemporal correlations and distribution patterns in the power grid data. The objective function of pre training is to minimize the reconstruction error between the predicted values and the true values. In the fine-tuning stage, based on the operation instructions recorded in the historical operation tickets and corresponding annotated data such as changes in the power grid status, supervised learning is used to adjust the parameters of the pre trained model. Adam is selected as the optimizer, the initial learning rate is set to 0.00001, the batch size is 32, and an early stop mechanism is adopted to prevent overfitting. The large model that has completed two-stage training can be applied to power grid state prediction and operation task generation.

3. Analysis of intelligent power grid operation task generation driven by large models

3.1. Performance evaluation of multidimensional verification based on rule engine

To verify the performance advantages of the multidimensional verification method for power grid data based on the rule engine, the study compared it with three other methods: the Ensemble Smoother Algorithm (ESA) multidimensional verification method, the graph partition spectral clustering multidimensional verification method, and the Generative Adversarial Network-Attention Mechanism (GAN-AM) multidimensional verification method. The ESA multidimensional verification method adopts an integrated smoothing algorithm framework, where the smoothing parameters are set to 15 set members, the perturbation scale factor is set to 0.8, and the state variables are updated using a stepwise iterative smoothing strategy, with a total of 4 iteration cycles. The multi-dimensional verification method for graph partitioning spectral clustering adopts a spectral clustering algorithm based on normalized cuts. The dimensionality reduction target dimension of the Turapuras matrix is set to 50, and the similarity matrix is calculated using a Gaussian kernel function. The kernel width parameter is determined within the range of 0.5 to 2.0 through grid search, and the number of clusters is set based on the square root of the number of grid nodes. The GAN-AM multidimensional verification method adopts an architecture that combines generative adversarial networks and attention mechanisms. The generator and discriminator each contain three fully connected hidden layers, with 256, 128, and 64 neurons in each layer. The attention module is embedded in the middle layer of the generator, using a scaled dot product attention mechanism. During the training process, the learning rate of both the generator and discriminator is set to 0.0002, the batch size is 32, the training epochs are 100, and the optimizer uses Adam. All comparative methods were trained using the same data partitioning ratio as the method proposed in this study and run in the same hardware environment to ensure the fairness of benchmark testing and the credibility of results. The experimental environment consisted of an Intel Core i7-10700K CPU, the Windows 10 operating system, 64GB of memory, an NVIDIA GTX 3060 GPU, and the use of 5G wireless communication technology to ensure efficient data transmission and processing. To maintain the authenticity and reliability of the experiment, the study used the SCADA and PMU datasets, both containing information on power system operating states. The large model used in the study is built on the Transformer architecture, which includes a multi-layer encoder decoder structure. The encoder is composed of 6 identical sub layers stacked together, each sub layer containing a multi head self attention mechanism module and a feedforward neural network module. Each module is followed by residual connections and layer normalization operations. The multi head self attention mechanism is set to 8 attention heads, each with a dimension of 64, and the overall hidden layer dimension of the model is 512. The feedforward neural network consists of two linear transformation layers, with the middle hidden layer having a dimension of 2048 and using the ReLU activation function. To capture long-distance dependencies in power grid time-series data, the model introduces position encoding in the input layer and explicitly encodes time step information using sine and cosine functions. In addition, the model did not use long short-term memory networks or graph neural networks as alternative or complementary architectures. This choice is driven by the study's focus on utilizing the self-attention mechanism of the Transformer to model global dependencies of multivariate time-series measurement data in the power grid. Although graph neural networks are suitable for graph data with clear topological structures, their computational complexity increases exponentially with the number of nodes, making it difficult to meet real-time requirements in large-scale power grid scenarios; Long short-term memory networks, on the other hand, are limited by their cyclic structure and suffer from gradient decay when capturing dependencies in ultra long time series, making it difficult to parallelize training. Therefore, the hybrid framework studied takes Transformer as the core architecture of the big model, and the rule engine and edge computing algorithm as auxiliary modules to undertake the functions of real-time rule matching and local fast response respectively. The above architecture parameter settings ensure the reproducibility of the model in power grid operation task generation tasks, and provide clear model basis for subsequent technical verification in actual deployment. The study tested the feature recognition accuracy of the four multidimensional verification methods, with the results shown in Figure 5.



(a) Test results of power grid data recognition accuracy in SCADA dataset

(b) Test results of power grid data recognition accuracy in PMU dataset

Figure 5. Test results of power grid data feature recognition accuracy

As shown in Figure 5(a), when the number of samples in the SCADA dataset reached 100, the rule engine-based power grid data multidimensional verification method achieved the highest feature recognition accuracy of 97.89%. As shown in Figure 5(b), when the number of samples in the PMU dataset reached 200, the highest feature recognition accuracy of the rule engine-based method was 96.78%. This is because the ESA method is based on a set smoothing framework, which essentially involves weighted averaging of multiple model prediction results. This method has limited ability to handle nonlinear feature interactions and is difficult to capture high-order coupling relationships between voltage, current, and power in power grid data. The graph partitioning spectral clustering method maps power grid data into graph structures and performs spectral decomposition. Its performance is highly dependent on the quality of the graph Laplacian matrix construction, and noise and outliers in power grid data can significantly compromise the accuracy of the similarity matrix, resulting in indistinct clustering boundaries. Although the GAN-AM method improves feature extraction capability through generative adversarial networks and attention mechanisms, there is a risk of pattern collapse in the adversarial training process between the generator and discriminator, which can easily overlook minority class feature patterns on imbalanced datasets. The proposed method utilizes a rule engine to pre-screen input data, removing obvious abnormal samples before performing feature recognition, thereby improving the signal-to-noise ratio of effective features. At the same time, the deterministic matching mechanism of the rule engine is not affected by sample imbalance problems. In summary, the rule engine-based multidimensional verification method accurately identified different power grid data features without being affected by external disturbances. The study further tested the balance verification effect of the rule engine-based method in comparison with the ESA, graph partition spectral clustering, and GAN-AM multidimensional verification methods. The results are shown in Figure 6.

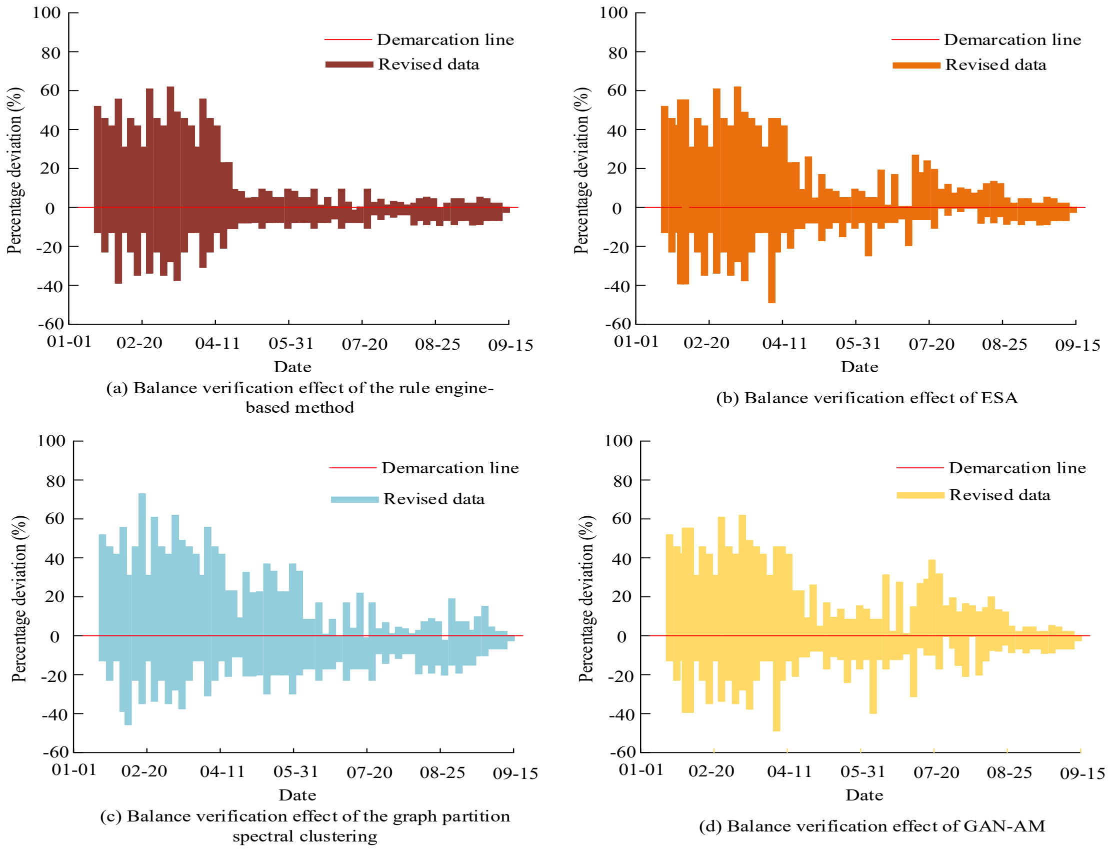
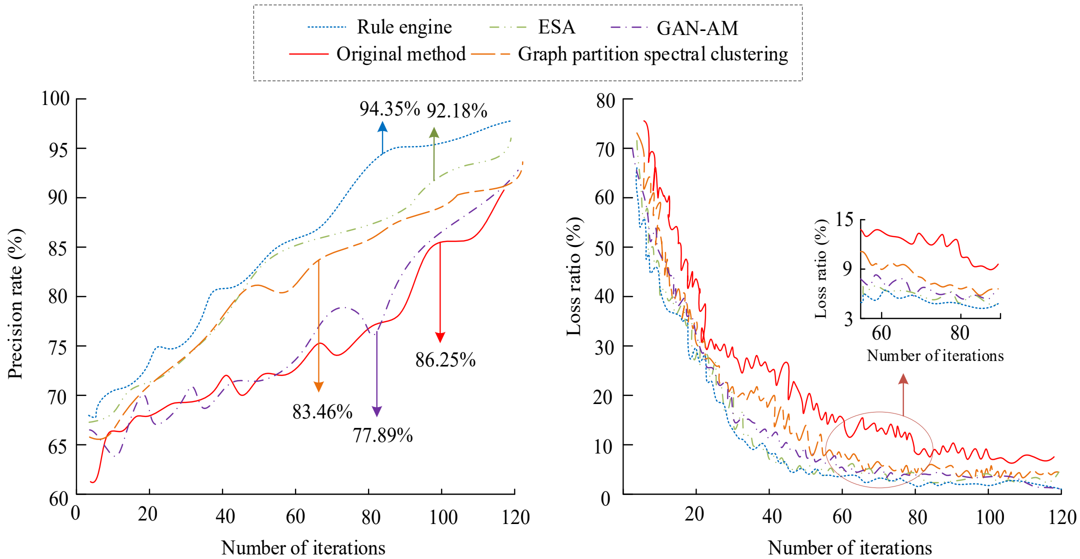


Figure 6. Balance check effect test results

As shown in Figure 6(a), on April 11, the rule engine-based multidimensional verification method exhibited relatively poor correction performance for historical power grid data, with the deviation percentage fluctuating between -40% and 60%. As shown in Figure 6(b), between July 20 and August 25, the ESA multidimensional verification method had a deviation percentage fluctuating between -15% and 25%. As shown in Figure 6(c), the graph partition spectral clustering method demonstrated poor balance correction performance for historical data before May 31. As shown in Figure 6(d), after August 25, the GAN-AM multidimensional verification method had a deviation percentage fluctuation range of -10% to 3%. The above results are due to the fact that the balance check of the research method relies on the predefined electrical quantity constraint rules in the rule engine. When the deviation patterns in historical data do not completely match the boundary conditions of the preset rules, the rule engine will generate judgment oscillations near the boundary, resulting in drastic fluctuations in the deviation percentage. In contrast, the generative adversarial mechanism of GAN-AM method can learn the intrinsic distribution of data, and its discriminator has continuity in distinguishing normal and abnormal patterns, resulting in smoother deviation fluctuations. However, the fluctuation amplitude of ESA method and graph partitioning spectral clustering method is between the two and exhibits randomness, because these two methods lack explicit modeling of temporal dependencies, and their correction results lack consistency constraints between different time points. The rule engine-based multidimensional verification method exhibited relatively strong correction performance for historical power grid data overall. To further validate the prediction accuracy of this method, the study compared it with the ESA, graph partition spectral clustering, GAN-AM, and the original method, testing their recognition accuracy and loss rate. The results are shown in Figure 7.



(a) Prediction accuracy rate results of different multidimensional checking methods

(b) Loss rate results of different multidimensional checking methods

Figure 7. Recognition accuracy and loss rate test results

As shown in Figure 7(a), after 82 iterations, the recognition accuracy of the rule engine-based multidimensional verification method reached 94.35%, increasing with the number of iterations. After 50 iterations, the recognition accuracy of the ESA multidimensional verification method was close to that of the rule engine-based method. As shown in Figure 7(b), after 60 iterations, the loss rate of the rule engine-based multidimensional verification method was 4.26%, which was 10.63% lower than the original method's loss rate of 14.89%. In summary, the rule engine-based multidimensional verification method accurately identified different types of power grid data while maintaining good convergence in loss rate reduction.

3.2. Validation of the improved task generation technology

After validating the performance of the rule engine-based multidimensional verification method, the study further analyzed the performance of the power grid operation task generation technology that combined this method with large-model-driven approaches. The study compared this technology with three others: fuzzy analytic hierarchy process, dual-criteria, and finite state machine methods. The cryptographic library used for the experiment was PBC 0.5.14, and the operating system was Ubuntu 22.04. The experimental datasets included the Gephi and openPDC datasets for training and testing. The four power grid operation task generation technologies were tested for operation response time and transmission rate, with the results shown in Table 1.

Table 1. Response time and transmission rate test results

Technology	Test item	Node 1	Node 2	Node 3	Node 4
Proposed technology	Response time /ms	8.2	8.4	8.6	8.3

	Transmission rate /Mbit·s^{-1}	22.1	22.2	23.2	20.9
Fuzzy analytic hierarchy process	Response time /ms	8.9	9.1	9.3	9.4
	Transmission rate/Mbit·s^{-1}	24.5	25.6	24.7	27.2
Dual-criteria	Response time /ms	9.1	9.3	9.5	9.6
	Transmission rate /Mbit·s^{-1}	23.4	23.6	24.7	23.2
Finite state machine	Response time /ms	9.3	9.7	9.4	9.2
	Transmission rate /Mbit·s^{-1}	24.2	25.6	24.8	24.3

As shown in Table 1, when testing Node 1, the proposed large-model-driven hybrid power grid operation task generation technology achieved an operation response time of 8.2ms and a transmission rate of 22.1 Mbit·s^{-1}. When testing Node 2, the operation response time and transmission rate were 8.4ms and 22.2 Mbit·s^{-1}, respectively. In contrast, the fuzzy analytic hierarchy process-based power grid operation task generation technology, when tested on Node 2, achieved an operation response time of 9.1ms and a transmission rate of 25.6 Mbit·s^{-1}. In summary, the proposed technology demonstrated faster operation response times and better decision-making capabilities for different nodes. Additionally, to further illustrate the diagnostic performance of the large-model-driven hybrid power grid operation task generation technology, the study compared it with the fuzzy analytic hierarchy process and dual-criteria power grid operation task generation technologies through a power grid fault diagnosis test. The results are shown in Figure 8.

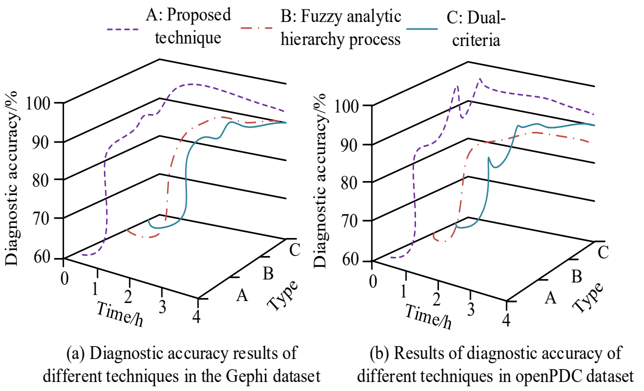


Figure 8. Power grid fault diagnosis test results

As shown in Figure 8(a), after 2 hours of testing, the fault diagnosis accuracy of the large-model-driven hybrid power grid operation task generation technology was 85.36%, reaching a peak of 97.23% over time. As shown in Figure 8(b), after 2 hours of testing, the fault diagnosis accuracy of this technology significantly improved to 95.78%. In contrast, the fault diagnosis accuracy of the dual-criteria power grid operation task generation technology was 78.97%, which was lower than that of the proposed technology. Among them, the fuzzy analytic hierarchy process relies on the judgment matrix constructed by expert experience, and its diagnostic ability is limited by the coverage of expert knowledge on fault modes. For compound faults or new faults that have not occurred in history, this method cannot adaptively adjust weights. The dual criteria method is based on predefined fault discrimination thresholds. Although the response speed is fast, the threshold setting is often based on typical operating conditions. When the power grid operating state deviates from typical operating conditions, a fixed threshold can lead to missed diagnosis or misdiagnosis. The large model in this research method has learned the temporal patterns of power grid fault evolution through pre training, and can dynamically adjust the discrimination criteria based on context. Therefore, it is superior to methods based on expert knowledge and fixed thresholds in terms of coverage breadth and diagnostic accuracy of fault types. In summary, the large-model-driven hybrid power grid operation task generation technology maintained high fault diagnosis accuracy during the power grid operation task process, improving overall scheduling efficiency and security. The study also evaluated the operation risk of the operation tickets generated by four power grid operation task generation technologies: large-model-driven hybrid, fuzzy analytic hierarchy process, dual-criteria, and finite state machine methods. The results are shown in Figure 9.

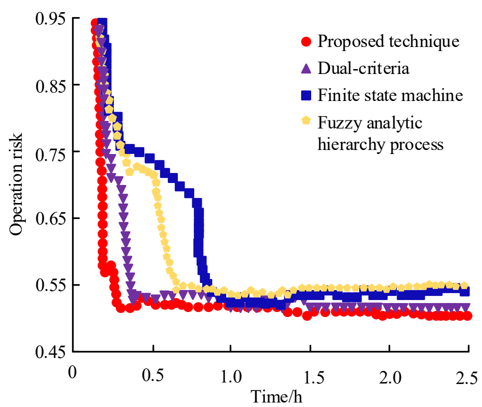


Figure 9. Operational risk test results

As shown in Figure 9(a), at 0.5 hours, the operation risk value of the operation tickets generated by the large-model-driven hybrid power grid operation task generation technology was 0.52. Between 1.0 and 2.5 hours, the operation risk value remained stable between 0.48 and 0.53. The operation risk value of the fuzzy analytic hierarchy process-based power grid operation task generation technology stabilized between 0.51 and 0.56 after 0.6 hours. The operation risk value of the dual-criteria power grid operation task generation technology fluctuated significantly between 1.0 and 1.8 hours, but after 2.0 hours, it remained stable. In summary, the operation tickets generated by the proposed technology effectively reduced operational risk and improved the efficiency of dispatch personnel.

4. Conclusion

To address issues regarding inaccurate grid data verification and high operational risks, this study proposes a large-model-driven task generation technology based on a rule engine for multidimensional grid data verification. During its construction, the rule engine separates business rules from code and, together with edge computing algorithms, predicts grid operation tasks to reduce operational risks. Experimental results demonstrate that with a sample size of 100, the feature recognition accuracy of the proposed multidimensional grid data verification method reaches 97.89%, while the feature recognition accuracy of the ESA, graph partition spectral clustering, and GAN-AM multidimensional verification methods are 95.45%, 91.28%, and 96.12%, respectively, all of which are lower than that of the proposed method. Furthermore, empirical analysis of the proposed large-model-driven grid operation task generation hybrid technology shows that when the test time is 2 hours, the fault diagnosis accuracy of the grid reached 97.23%. In comparison, the fault diagnosis accuracy of the fuzzy analytic hierarchy process and dual-criteria grid operation task generation methods are 90.03% and 91.04%, respectively. The above results verify the effectiveness and reliability of the exploration method in complex power grid regulation scenarios, which not only enriches the theoretical system in related fields, but also provides strong support for practical applications. However, there are still limitations in the research, and the classification of power grid risk sources in the experiment has not been systematically carried out, which has not fully covered various potential risks. Future research should focus on strengthening fine-grained classification and intelligent recognition of multi-source risk factors, and emergency response and autonomous decision-making mechanisms under extreme working conditions can be explored. Finally, the integration with emerging technologies such as 5G and digital twins can be promoted to build a more intelligent and robust future power grid operation system.

Acknowledgements
This work was supported by the Science and Technology Project of China Southern Power Grid, with the project number 031900KC23090056.

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