A Deep Reinforcement Learning and Evolutionary Optimization-Based Collaborative Control Network for Power Systems with Multi-Terminal Information Fusion

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To improve the control performance of power systems in complex environments, this study proposes a cooperative control method integrating multi-terminal information acquisition, deep reinforcement learning (Deep Deterministic Policy Gradient, (DDPG)) and evolutionary algorithms (Particle Swarm Optimization (PSO), Genetic Algorithm (GA)). The constructed control framework integrates multi-source monitoring data, realizes state information enhancement through feature-level fusion, and optimizes control decisions using an evolutionary reinforcement learning strategy. Experiments are carried out on a power system simulation platform built in Simulink. The data used are generated by the platform simulation, covering the dynamic operation of a 50-node system under typical disturbance conditions, referenced to the parameter configuration of the State Grid Manual, and verified by the experience of power system engineers. Typical operating conditions such as wind power integration, load mutation, and sensor missing are simulated to evaluate the control effect and robustness of the model. The results show that the proposed method is superior to existing methods such as Transformer-based Control Algorithm (TCA), Graph Neural Network (GNN), and Reinforcement Learning with Curiosity-driven Exploration (RLCE) in terms of voltage prediction accuracy (92.5%), F1 score (0.912), and system stability (97.5%). The training convergence speed is improved by about 15%, and the control performance is still maintained above 90% in the scenario of 20% sensor missing. The proposed method achieves an effective balance between the flexibility of reinforcement learning and the evolutionary search capability, showing strong promotion value and engineering application potential.

Povzetek: Študija predlaga kombinirano metodo globokega ojačitvenega učenja in evolucijskih algoritmov za vodenje elektroenergetskih sistemov, ki izboljša natančnost, stabilnost in robustnost tudi v zahtevnih pogojih.

1 Introduction

With the rapid development of social economy and the continuous growth of energy demand, the stability, efficiency and safety of power system have become the focus of attention today. Traditional power system control is facing complex challenges, such as the expansion of power grid scale, distributed energy access, and increased intelligent demand [1]. Therefore, how to realize the coordinated control of power system through innovative technologies and methods has become an important problem that needs to be solved urgently in the field of power engineering. Collaborative control of power system refers to the real-time regulation and optimization of system operation state through information sharing and coordination among multiple nodes [2]. With the rapid development of information technology, multi-terminal information fusion has become the key to improve the control efficiency of power system. Multi-end information includes not only monitoring data from traditional power equipment, but also big data information obtained from emerging technologies such as smart sensors, Internet of Things (IoT) devices and cloud computing platforms [3, 4].

At present, with the deep integration of information technology and power system, the collaborative control technology of power system has made remarkable progress. The traditional control mode of power system mainly depends on centralized monitoring and single control strategy, and it is difficult to effectively meet the challenges of increasingly complex power grid structure and load fluctuation [5]. Therefore, researchers gradually turn to collaborative control network based on multi-terminal information fusion to improve the response speed, reliability and energy efficiency of the system. On the technical level, many cutting-edge algorithms, such as deep learning, reinforcement learning and distributed optimization algorithms, are widely used in the collaborative control of power systems to realize intelligent data processing and real-time decision optimization [6]. For example, deep learning shows good application potential in power grid load forecasting and anomaly detection, while reinforcement learning optimizes the operation strategy of power system by simulating the interactive learning between agents and the environment [7]. In addition, many international research institutions and enterprises have invested in the research and development and application of smart grid technology, and put forward their own unique collaborative control schemes and technological innovations, such as the smart grid project in the United States and the super grid initiative in the European Union [8]. These practices and experiences provide valuable reference for this study, and provide rich theoretical and empirical support for the intelligent upgrading and optimal development of China's power system.

This study aims to explore the cooperative control network of power system based on multi-terminal information fusion, focusing on how to realize the information interaction and coordination among the nodes of power system operation through advanced algorithm and model design. Specifically, this study introduces sensor network and data processing technology, and combines advanced algorithms such as deep learning and reinforcement learning to construct an efficient collaborative control strategy. Through experimental verification and data analysis, the application effect and potential advantages of new technology in power system are evaluated, which provides new ideas and empirical support for technological innovation and development in power engineering field. In addition, the research results of this study are significant for improving the operation efficiency of power system, and have far-reaching influence on promoting intelligent energy management, promoting energy interconnection and realizing sustainable energy development. By exploring the application of multi-terminal information fusion technology in power system, this study aims to contribute to the future smart grid construction and the progress of power engineering technology, and promote the development of power industry in a safer, more efficient and sustainable direction. Based on the above analysis, this study sets three main objectives: improving voltage prediction accuracy, shortening system recovery time after faults, and maintaining low energy consumption. The proposed method adopts a multi-terminal information fusion approach based on Deep Reinforcement Learning (DRL) to achieve these objectives. Different from existing studies, this study proposes a multi-terminal information fusion control model that integrates DRL and evolutionary algorithms. By constructing a heterogeneous information fusion architecture, it realizes the synchronous fusion of high-frequency data from Phasor Measurement Units (PMUs), sensors, and Internet of Things (IoT) devices, and uses this to drive the dynamic optimization of control strategies. At the same time, the study embeds Deep Deterministic Policy Gradient (DDPG) and Particle Swarm Optimization (PSO) into the power collaborative control process for the first time, building an end-to-end data-driven control network. This method improves control accuracy and response speed, and enhances the system's adaptive ability to abnormal working conditions. This study achieves systematic breakthroughs in method architecture, control mechanism, and performance evaluation, providing theoretical references and engineering demonstration value for the structural design and regulation algorithms of future smart grids.

2 Literature review

The development of power system collaborative control has gone through several stages, from the initial centralized control to distributed collaborative evolution to meet the challenges of complex power grid structure and intelligent demand [9]. Early researchers mainly focused on how to optimize the traditional control strategy of power system, and realized the optimal regulation of system operation state through mathematical modeling and optimization theory [10]. With the expansion of power system scale and the increase of complexity, the traditional centralized control mode gradually shows its limitations, which cannot effectively deal with the problems of distributed energy access and load fluctuation in the power grid [11]. Therefore, the research gradually turns to the direction of multi-node cooperative control, aiming at improving the response speed and stability of the system through information sharing and coordination optimization [12]. However, when traditional centralized architectures cope with multi-node communication delays and dynamic fluctuations of distributed energy sources, they have problems such as excessive load on central nodes, accumulated information delays, and insufficient fault tolerance. In recent years, with the rapid development of artificial intelligence (AI) technology, the coordinated control of power system has ushered in new development opportunities [13]. The application of deep learning algorithm improves the ability of power load forecasting and system state identification [14]. Meanwhile, reinforcement learning technology optimizes the dynamic regulation strategy of power system through interactive learning between agents and environment, and realizes independent learning and adaptability [15, 16]. Alhamrouni et al. showed that the cooperative control method of power system based on AI technology had obvious advantages in improving system efficiency and reliability [17]. Although deep learning and reinforcement learning have improved prediction and control accuracy, most studies still remain at the single-source data level and fail to effectively address the real-time optimization problem under multi-source heterogeneous data fusion.

The application of multi-terminal information fusion technology in power system is becoming an important means to improve the intelligence and efficiency of the system. By integrating multi-source data from traditional power equipment, smart sensors and cloud computing platforms, researchers explore how to realize information sharing and intelligent decision-making among nodes of power system [18]. In related research, many research teams have adopted different research methods to deal with the fusion and processing of multi-terminal information in power system. For example, Shakiba et al. used machine learning algorithm to analyze the monitoring data of power grid and proposed a load forecasting model based on neural network, which effectively improved the forecasting accuracy and system response speed [19]. Meanwhile, Marín-Quintero et al. used distributed data mining technology, combined with Internet of Things (IoT) technology to realize remote monitoring and management of power equipment, and optimized the power grid operation efficiency and resource utilization [20]. On the other hand, the application of multi-terminal information fusion technology in smart grid construction has also achieved remarkable results. Arsad et al. proposed a smart grid management platform based on cloud computing and big data analysis. By integrating data from multiple smart sensors, real-time monitoring and intelligent regulation of power system were realized, which provided strong support for the safe and stable operation of power grid [21]. By integrating and utilizing multi-source data, comprehensive monitoring and accurate prediction of power system state can be realized, which provided solid technical support for the safety and reliability of system operation [22]. However, with the complexity of power system structure and the increase of data volume, how to effectively process and apply big data has become an important challenge for future research, which needs further in-depth discussion and solution.

To more clearly present the comparison of different control methods in terms of data usage types, performance, and shortcomings, this study constructs Table 1 to systematically compare current mainstream methods to highlight the research necessity of the proposed method.

Table 1: Comparative analysis of various control methods in multi-terminal data processing of power system.

Method category	Representative reference	Data type	Control performance index	Existing problem
Traditional centralized control	[10], [11]	Single source data (such as voltage/current)	Fast optimization speed; Suitable for small-scale systems	Rely on the central node, it cannot deal with multi-point disturbance in real time and has poor fault tolerance.
Graph neural network (GNN)	[12], [20]	Local topological data +state characteristics	Strong topological modeling ability; Suitable for mesh structure	Limited ability to process real-time multi-source data; Complex training
Deep reinforcement learning (DRL)	[15], [17]	High-dimensional state data (such as load and frequency)	Strong adaptive learning ability; High precision	Most of them are single-source inputs; Lack of dynamic data fusion mechanism
Multi-terminal information fusion +machine learning	[18], [19], [21]	Multi-source heterogeneous data	Improved forecasting accuracy (voltage, load)	Most of them are static fusion; Lack of real-time feedback mechanism and optimization means

In Table 1, traditional methods have certain advantages in early power system optimization, but they have significant deficiencies when facing the demand for dynamic fusion of multi-source data. Emerging graph neural network and DRL models perform well in modeling capabilities and adaptability, but usually fail to solve the problems of heterogeneous data sources and multi-node synchronous control. Although multi-terminal fusion methods have achieved initial results, they lack integration with reinforcement learning and are difficult to realize real-time optimization of control strategies. Therefore, constructing a model that integrates multi-source data perception capability and adaptive control optimization capability is a key breakthrough direction in current research.

In summary, although existing studies have made significant progress in power system collaborative control and multi-terminal information fusion, there are still systemic shortcomings: Most traditional control strategies rely on centralized structures, which are difficult to meet the real-time coordination needs under distributed energy access and prone to communication bottlenecks and single-point failures. Although intelligent control methods based on deep learning and reinforcement learning have improved prediction and optimization capabilities, most are still limited to single-source data scenarios and cannot fully explore the associated features of multi-terminal heterogeneous data. Existing multi-terminal information fusion models often perform static fusion at the feature layer or decision layer, lacking adaptive mechanisms. This leads to insufficient generalization of control strategies under dynamic operating conditions. To address the above issues, this study proposes a multi-terminal information fusion collaborative control network based on DRL and evolutionary optimization algorithms. By integrating real-time decision-making driven by multi-source data and adaptive parameter optimization, this study achieves efficient and stable control of complex power systems, making up for the shortcomings of existing studies in real-time performance, robustness, and system intelligence.

3 Research method of power system collaborative control network

This study aims to improve the cooperative control performance of power systems through multi-terminal information fusion and DRL technologies. The design of the research method focuses on the following three specific research questions (RQs): Research Question 1 (RQ1): Can the proposed method significantly outperform existing algorithms in voltage prediction accuracy? Research Question 2 (RQ2): Under abnormal operating conditions such as faults or load mutations, can this method shorten the system recovery time? Research Question 3 (RQ3): While maintaining the stability of system control, does this method have low energy consumption?

To address the above questions, this study proposes a control method integrating DRL optimization, adaptive reward function design, and evolutionary algorithm strategies, and verifies its effectiveness through experiments under normal and abnormal scenarios.

3.1 Multi-terminal information acquisition and processing technology

In multi-terminal information fusion cooperative control network of power system, information acquisition and processing technology is the key to realize efficient and stable operation of the system.

To ensure that the information of each node in the power system can be collected timely and accurately, it is very important to select and arrange appropriate sensor networks and data acquisition equipment. New sensors widely used in modern power systems include smart meters, Phasor Measurement Unit (PMU), voltage and current sensors, etc. These sensors can monitor the running state of power system in real time and collect key parameters such as voltage, current and power factor. The layout of sensor networks needs to consider the coverage, data transmission speed and reliability. Wireless Sensor Network (WSN) and IoT technologies are usually adopted to ensure the comprehensiveness and accuracy of data collection through reasonable planning of node distribution [23].

Specifically, this study designs a multi-level sensor network layout scheme. The main sensors used in the network include: Smart Energy (SE)-800 smart meters: Used to monitor voltage, current, power factor, etc. PMUs: Used to collect synchronized phasor data. Temperature Sensor (TS)-200 temperature sensors: Used to monitor the temperature of substations or outdoor environments. Other conventional current and voltage sensors. In terms of installation locations: PMUs are mainly deployed at key substations and transmission nodes to ensure time-domain synchronization. SE-800 smart meters are arranged at user access terminals and load nodes. TS-200 sensors are installed in environment-sensitive areas such as outdoor switch stations. Regarding data collection frequency: The PMU is set to 30 times per second (30Hz). The SE-800 is set to 5 times per minute. The TS-200 is set to 1 time per minute. The frequency is dynamically configured according to device characteristics and application scenarios. To ensure comprehensive data coverage, the sensor layout adopts a redundancy mechanism, with at least two sensors from different sources deployed at each key node. For data transmission: A hybrid communication protocol of ZigBee and LoRa is used. ZigBee (2.4GHz) is applied for short-distance nodes, while LoRa (433MHz) is used between long-distance nodes and the main control center. All data is uniformly connected to edge computing nodes based on the Message Queuing Telemetry Transport (MQTT) protocol, forming a low-power consumption and high-reliability transmission link. In addition, the collected data is uploaded to the cloud platform (Control Processor (CP)-500) at regular intervals after edge processing, forming a unified data lake to provide high-quality data support for subsequent deep learning and control decision-making.

In the power system, there are various data sources, including meteorological data, market transaction data and user load data, in addition to the traditional power equipment data. To effectively fuse these multi-source data, many advanced data fusion technologies are applied. Firstly, the multi-source data fusion algorithm based on machine learning is adopted, and the comprehensive utilization of data and information enhancement are realized through correlation analysis and feature extraction of data from different sources. Secondly, deep learning models, such as Convolutional Neural Network (CNN) and Long Short-Term Memory (LSTM), are used to process structured and unstructured data to improve the accuracy and real-time performance of data fusion. In addition, the introduction of blockchain technology also enhances the security and transparency in the process of data fusion.

In the process of data acquisition and fusion, data preprocessing and feature extraction are important steps to ensure data quality and analysis effect. Data preprocessing includes data cleaning, missing value filling, abnormal value detection and processing. Specific methods include standardization and normalization to eliminate dimensional differences between different data sources and ensure data consistency and comparability. In the standardization process, this study adopts the Z-score standardization method to perform a linear transformation on various types of raw numerical data, making their mean 0 and standard deviation 1. For non-normally distributed data, the Min-Max normalization method is used to map the data to the [0,1] interval, which enhances the model's robustness to extreme values. Data normalization is suitable for processing positively skewed distribution features such as response time and energy consumption in control models. By combining these two methods, the model's generalization ability and stability in a multi-source data environment are enhanced.

In the aspect of feature extraction, the key features are extracted from the original data by statistical analysis, Principal Component Analysis (PCA) and independent component analysis (ICA) to reduce the data dimension and keep the information that has important influence on the running state of the system. Specifically, PCA calculates the covariance matrix of each feature and extracts the principal components with the largest variance. This effectively reduces data dimensionality while retaining information of highly correlated features such as voltage, current, and load, improving model operation efficiency and reducing the risk of overfitting. ICA, on the other hand, has unique advantages in processing monitoring signals of power systems. It is particularly suitable for separating independent potential sources from multi-source mixed signals, thereby improving the purity and accuracy of feature extraction. In addition, using the Autoencoder and Recurrent Neural Network (RNN) based on deep learning, people can automatically learn and extract complex features from massive data, and improve the efficiency and accuracy of feature extraction, as shown in Figure 1.

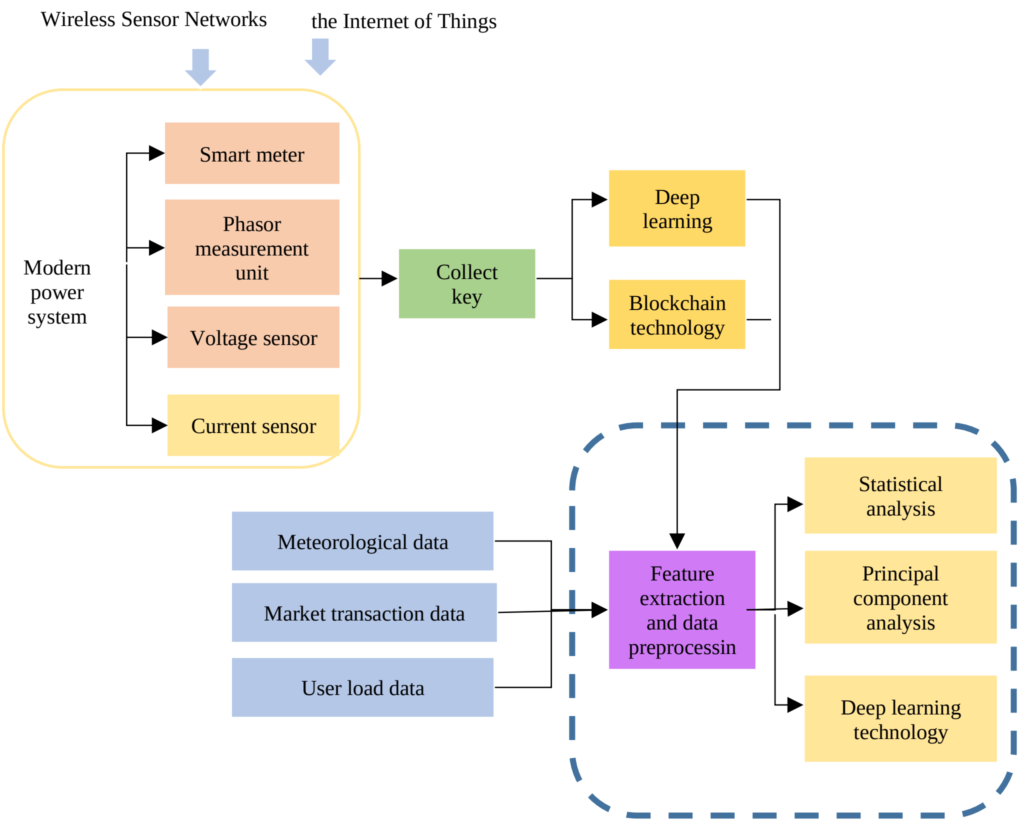

Figure 1: Multi-terminal information acquisition and processing technology.

To achieve efficient fusion and cooperative control of multi-source data, this study designs a three-level data fusion architecture, including the Raw Data Level, Feature Level, and Decision Level, as shown in Figure 2.

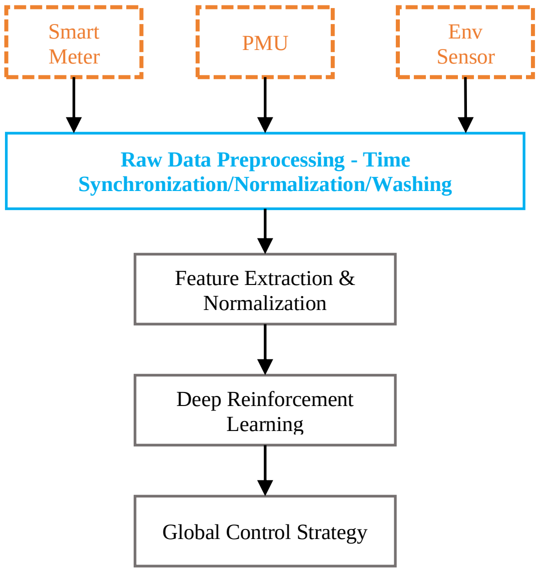

Figure 2: Multi-terminal data fusion architecture.

In Figure 2: Raw Data Level: Collects raw data from devices such as smart meters, PMUs, and temperature-humidity sensors, and achieves synchronization through a unified timestamp mechanism. Feature Level: After standardizing, normalizing, and encoding the data collected by different devices, key features (e.g., voltage fluctuation rate, load change trend, temperature change rate) are extracted. Decision Level: Various features are input into the DRL controller for strategy generation and action selection, ultimately forming global control decisions. The fusion method combines heterogeneous feature-level fusion with joint strategy optimization. All types of data undergo normalization and vector expression at the feature level, and are jointly sent to the strategy network through the fusion module for unified modeling and training. This improves the model's generalization ability and robustness under multiple operating conditions.

3.2 Design and modeling method of collaborative control network

In this study, a design and modeling method of power system collaborative control network based on multi-terminal information fusion is proposed to improve the intelligence, stability and operation efficiency of power system.

To achieve efficient collaborative control, this study designs a control strategy based on DRL. Specifically, PCA calculates the covariance matrix of each feature and extracts the principal components with the largest variance. This reduces data dimensionality while retaining information of highly correlated features such as voltage, current, and load, which improves the model's operating efficiency and reduces the risk of overfitting. ICA, however, has unique advantages in processing monitoring signals in power systems. It is particularly suitable for separating independent potential sources from multi-source mixed signals. For example, separating fault sources from background noise in voltage disturbance signals. This separation improves the purity and accuracy of feature extraction, which is significant for enhancing the stability and robustness of control strategies.

The agent continuously optimizes the control strategy through interactive learning in the simulation environment, and the specific steps are as follows:

1. Definition of state space and action space

State space S represents the operating state of power system, including voltage, current, power, etc. Action space a represents control operations, such as adjusting generator output and load dispatching.

2. Reward function design

The reward function $R(s,a)$ is designed to evaluate the effect of each action, and it is defined as equation (1) by comprehensively considering energy consumption, system stability and response speed.

$$R(s,a) = -\alpha E(s,a) + \beta S(s,a) - \gamma T(s,a) \quad (1)$$

α, β, and γ are weight coefficients. $E(s,a) = \sum_{i=1}^{N} \frac{I_i \cdot V_i^2}{R_i}$, $S(s,a) = \frac{1}{\Delta U^2 + \Delta f^2}$, $T(s,a) = t_{\text{recovery}}$. $E(s,a)$ represents the power loss at the i-th node. I is current, V is voltage, and R is equivalent resistance. $S(s,a)$ uses voltage deviation ΔU and frequency deviation Δf to measure system stability. $T(s,a)$ is the time for the system to recover from disturbances, which is used to evaluate response speed.

In the parameter design of the reward function, the weight coefficients α, β, and γ are determined through multi-objective optimization based on the importance of the power system's operation goals. Specifically, α reflects the influence weight of energy consumption in the control strategy, β measures the priority of system stability, and γ corresponds to the importance of system response time. The initial weight values are set to α=0.4, β=0.4, and γ=0.2 based on expert experience, and are adaptively adjusted in the early stage of training through genetic algorithm (GA) to ensure the dynamic balance of the reward function under different operating conditions.

Energy consumption $E(s,a)$ is calculated based on the power loss of system nodes. System stability $S(s,a)$ is defined by the inverse square of voltage fluctuation rate and frequency deviation, which encourages control strategies to maintain stable operation. Response time $T(s,a)$ reflects the time delay from the activation of control commands to the restoration of system state balance. The dynamic adjustment of weights enables the DRL agent to adaptively balance the goals of energy conservation and stability in different scenarios, thereby improving global optimization capabilities and strategy convergence speed.

3. The application of Deep Q-Network (DQN)

The Q-value function is approximated by the deep neural network (DNN), and the updated equation is (2):

$$Q(s,a) \leftarrow Q(s,a) + \alpha\left(r + \gamma \max_{a'} Q(s',a') - Q(s,a)\right) \quad (2)$$

4. Training and optimization

Experience playback and fixed Q target network are used to improve the training stability and convergence speed.

To make full use of multi-source data, this study adopts a series of optimization algorithms to optimize the control network, including reinforcement learning and evolution algorithms.

Using the deep deterministic policy gradient (DDPG) algorithm, combined with the characteristics of continuous action space, the control strategy is optimized through the actor-critic structure, as shown in equations (3)-(5):

$$L(\theta^Q) = \mathbb{E}_{s_t\sim\rho^\beta, a_t\sim\pi(s_t)}[(Q(s_t,a_t \mid \theta^Q) - y_t)^2] \quad (3)$$

$$y_t = r_t + \gamma Q'\left(s_{t+1}, \pi'\left(s_{t+1} \mid \theta^{\pi'}\right) \mid \theta^{Q'}\right) \quad (4)$$

$$\nabla_{\theta^\pi} J \approx \mathbb{E}_{s_t\sim\rho^3}\left[\nabla_a Q(s,a \mid \theta^Q)|_{a=\pi(s|\theta^\pi)} \nabla_{\theta^*}\pi(s \mid \theta^\pi)\right] \quad (5)$$

$L(\theta^Q)$ is the loss function. θ^Q is the parameter of the critic network. s_t is the state at time *t*. ρ^β is the behavior policy distribution. a_t is the action at time *t*. $\pi(s_t)$ is the policy network. y_t is the target value. r_t is the reward at time *t*. γ is the discount factor. Q' is the state of the critic network at time *t*+1. π' is the target policy network. $\theta^{\pi'}$ is the parameter of the target policy network. θ^π is the parameter of the policy network, and J is the optimization objective. Equation (3) represents the loss function of the critic network, which updates the parameters of the critic network by minimizing the Q-value error. Equation (4) is the target value calculation method, which integrates the current reward and future state value to estimate the true Q-value.

Compared with common strategy optimization algorithms such as Proximal Policy Optimization (PPO) and Asynchronous Advantage Actor-Critic (A3C), DDPG has significant advantages in handling continuous control tasks. Specifically, PPO is more suitable for discrete action spaces or tasks with low tolerance for strategy changes. A3C, on the other hand, is more inclined to distributed asynchronous training and has certain fluctuations in stability. In contrast, DDPG can achieve fine-grained strategy optimization in high-dimensional continuous action spaces, making it applicable to scenarios in power systems that require precise regulation, such as voltage regulation and frequency control. In addition, the "actor-critic" architecture and experience replay mechanism adopted by DDPG also significantly improve learning efficiency and strategy smoothness, enabling it to have higher stability and adaptability in dynamic power grid environments. Therefore, selecting DDPG as the core strategy optimization algorithm is more in line with the actual needs of power system control.

To enhance the global optimization capability of control strategies and the efficiency of parameter convergence, this study introduces a collaborative optimization mechanism combining GA and PSO. The collaborative process is as follows: First, GA is used for population initialization, individual selection, and crossover mutation to obtain a group of relatively optimal individuals. These optimal individuals are then used as the initial particle swarm for PSO. On this basis, PSO performs local adjustments of velocity and position to further explore the optimal solution region. The two algorithms iterate alternately: GA provides global exploration capability, while PSO achieves accelerated convergence near local solutions. Through this collaborative strategy, the global optimization advantages of GA and the fast local search capability of PSO are integrated, which avoids falling into local optima and improves the robustness and adaptability of control strategies in complex power grid environments. The speed and position updating formulas of PSO algorithm are equation (6) and equation (7):

$$v_i^{k+1} = \omega v_i^k + c_1 r_1\left(p_i^{best} - x_i^k\right) + c_2 r_2\left(g^{\text{best}} - x_i^k\right) \quad (6)$$

$$x_i^{k+1} = x_i^k + v_i^{k+1} \quad (7)$$

v_i^{k+1} is the velocity of particle *i* at the *k*+1th iteration. ω is the inertia weight. v_i^k is the velocity of particle *i* at the *k*th iteration. c_1 and c_2 are acceleration constants. r_1 and r_2 are random numbers between [0,1]. p_i^{best} is the historical best position of particle *i*. x_i^k is the position of particle i at the *k*th iteration. g^{best} is the global best position, and x_i^{k+1} is the position of particle i at the *k*+1th iteration.

In the design of collaborative control network, the optimization of structure and parameters is the core link. In this study, the mathematical modeling method is used to optimize the design. Firstly, network structure modeling: the control network consists of multiple nodes, and each node corresponds to a power device or sensor. The network structure can be expressed as a directed graph $G = (V, E)$. V is the node set and E is the edge set, and the edge weight indicates the information transmission efficiency between nodes.

Secondly, parameter optimization modeling: parameter optimization includes node parameters and edge parameters. The node parameter θ_v represents the control parameter of each node, and the edge parameter θ_e represents the information transmission parameter. The optimization objective function is equation (8):

$$\min_{\theta_v,\theta_e} J(\theta_v,\theta_e) = \sum_{v\in V} C_v(\theta_v) + \sum_{e\in E} C_e(\theta_e) \quad (8)$$

$C_v(\theta_v)$ and $C_e(\theta_e)$ are cost functions of nodes and edges, respectively, which reflect performance indexes such as energy consumption and delay.

Finally, constraints: constraints include voltage, current and other power system operation restrictions: $g(x,u) \le 0$.

To ensure the reproducibility and tuning efficiency of the reinforcement learning model, this study sets key DDPG hyperparameters as follows: Learning rate = 0.001, which controls the weight update amplitude of the neural network. Discount factor γ = 0.95, which measures the impact of future rewards on the current policy value. Replay Buffer size = 100,000, used to store historical interaction samples. Batch Size = 64, indicating the number of samples sampled from the experience pool in each training round. Fixed target network update mechanism: the target network is updated every 10 steps to stabilize the training process. These parameter settings are based on existing research experience and experimental verification to achieve the convergence and stability of the model in complex power system scenarios.

3.3 Experimental setup and data acquisition mode

This experiment is conducted in a simulated power system environment, and an experimental platform with multi-terminal information acquisition and processing equipment is built. The specific equipment is shown in Table 2:

Table 2: Experimental equipment.

Device name	Functional description
Smart electric meter	Real-time monitoring of voltage, current, power and other data.
Temperature sensor	Monitor the ambient temperature and analyze the influence of the environment on power equipment.
Power router	Data transmission and communication
Data acquisition unit	Collect and store multi-source data
Cloud computing platform	Conduct large-scale data processing and analysis

By integrating the above equipment, the experimental platform realizes the state monitoring and data acquisition of each node of the power system, and ensures the comprehensiveness and accuracy of the experimental data. The experimental platform is deployed on a local high-performance computing server, with the following hardware configuration: CPU: Intel Xeon Gold 6226R @ 2.9GHz. Memory: 256GB. GPU: NVIDIA Tesla V100 32GB. Storage: 10TB SSD array. The software environment is as follows: Operating System: Ubuntu 20.04 LTS. Main Software & Libraries: Python 3.10 (with dependencies including Pandas, NumPy, Scikit-learn, TensorFlow 2.13). Matlab R2022b (for modeling and control algorithm simulation). MySQL 8.0 (for structured storage and management of experimental data). Integrated environment of Docker and JupyterLab (for distributed model training and visual display). All experiments are deployed and run through automated scripts, and each round of training and simulation results is recorded via a log system to support experimental reproducibility and data traceability.

In the process of data acquisition, people face the following technical challenges and put forward corresponding solutions. Specifically, because the sampling frequency of each sensor is different, the data is not synchronized. The solution is to use the time stamp function in the data collector to process the data in a unified time axis. The distribution of multi-terminal devices may cause data transmission delay. By optimizing the transmission algorithm of power router and using efficient transmission protocol, the transmission delay is reduced. The data format and accuracy of different devices are inconsistent. By presetting the data standardization module in the data collector, the data format conversion and precision unification are carried out.

The dataset used in this experiment is derived from actual collected data in a simulated power system platform, covering a 30-day period from June 1 to June 30, 2023. A total of 50 sensor nodes is deployed in the system, including: 20 smart meters, 10 temperature and humidity sensors, 10 load monitoring terminals and 10 PMU devices. Approximately 50GB of data is collected daily, with a total of about 1.5TB. The dataset covers key variables such as voltage, current, active/reactive power, load changes, and environmental information.

In the data preprocessing stage, Python's Pandas library is used for missing value imputation (mean imputation), outlier detection (based on the Z-score algorithm), and outlier correction. Data synchronization adopts a unified timestamp mechanism to ensure alignment of data sampled at different frequencies. In the feature encoding stage, One-Hot encoding is applied to process discrete state signals, and continuous variables are uniformly standardized. To ensure the model's generalization performance, the dataset is divided into a training set (80%), validation set (10%), and test set (10%) according to the time series.

The data collected this time specifically include: voltage data (real-time monitoring the voltage fluctuation of each node), current data (recording the current change of each node), power data (including active power and reactive power, reflecting the power transmission of the system), environmental data (temperature, humidity, etc., analyzing the influence of the environment on power equipment), and load data (load situation of each node, including dynamic load change). Among them, voltage, current and power data are collected once every second. Environmental data is collected once every minute. Load data is collected every 5 minutes. The amount of data collected every day is about 50GB, including the real-time data of all nodes. The experimental period is 30 days, and the total data is about 1.5TB. The dataset is divided into training set, verification set and test set =8:1:1.

To ensure the representativeness and rationality of the collected data in simulation experiments, the data acquisition scheme and variable settings of this study refer to the typical operating condition settings in the State Grid Operation Manual and existing research [24, 25]. During the experimental design phase, two engineers with more than 10 years of experience in power system operation were invited to review the simulation scenarios and data variables. Experts confirmed that the indicators covered by the data, such as voltage, current, and load fluctuation range, can relatively truly simulate the operating status of the actual distribution system, thereby verifying the rationality and availability of the dataset. Although the simulation platform has high system dynamic response and equipment modeling capabilities, the obtained data are still "high-fidelity simulated data" rather than directly from the actual power grid operation system. Therefore, before being promoted to a larger-scale power grid or a more complex operating environment, it is necessary to further verify the model's generalization ability through real-grid data. At the same time, the platform cannot simulate all possible nonlinear faults or extreme operating states. In the future, integration testing with industrial systems should be strengthened to further evaluate the model's stability and robustness. The experimental data are constructed based on the Simulink model, and the simulation parameters refer to the State Grid Dispatching Operation Regulations and are assisted and verified by two power industry engineers to ensure the engineering rationality of the simulation data.

To effectively analyze the collected data, this study adopts a variety of data analysis tools and methods, as shown in Table 3:

Table 3: Data acquisition and analysis tools.

Tools/methods	Description
Python programming	Python is used for data processing and analysis. The main libraries include Pandas, NumPy, etc.
Matlab	Conduct complex mathematical modeling and simulation analysis.
R programming language	Conduct statistical analysis and data visualization.
Database	Use Mysql for data storage and management
Machine learning	Use Scikit-learn and TensorFlow for data mining and model training.

In the process of data analysis, the first is data cleaning and preprocessing: the original data is cleaned and preprocessed through Python Pandas library, including missing value processing, abnormal value detection and correction. Secondly, feature extraction and selection: Use Python's Scikit-learn library to extract and select features to ensure the effectiveness of data analysis. Data modeling and simulation: Use Matlab to model and simulate the processed data, and analyze the effects of different control strategies.

4 Collaborative control network design and modeling result analysis

4.1 Effect analysis of multi-source data fusion

In the process of multi-terminal information fusion, combining data from different sources can significantly improve the performance of power system collaborative control network. The performance comparison before and after multi-source data fusion is shown in Figure 3:

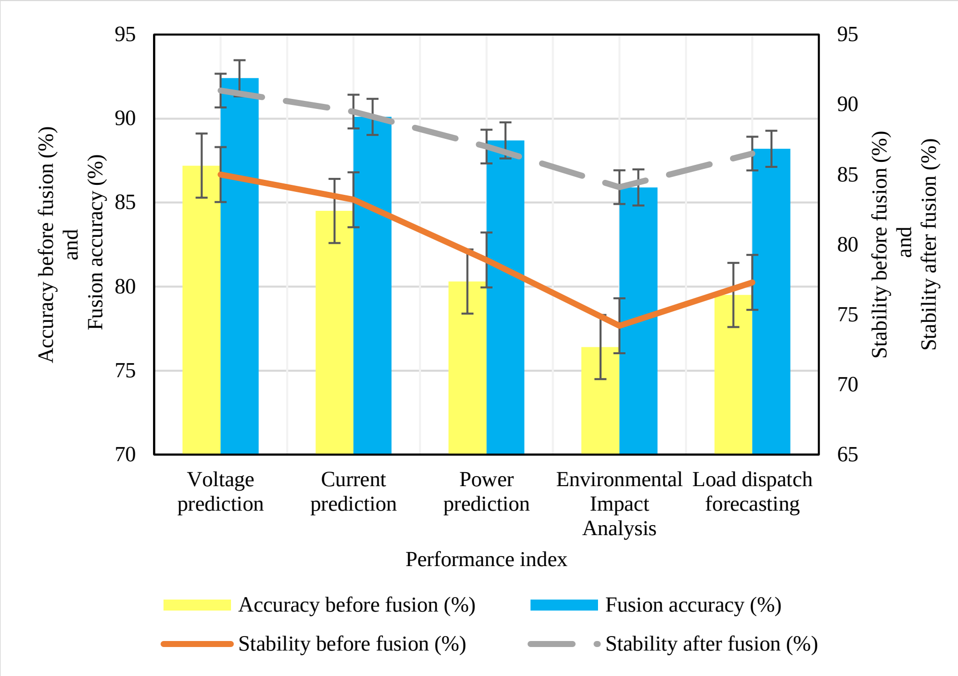

Figure 3: Performance comparison before and after multi-source data fusion.

According to Figure 3, after data fusion, the accuracy and stability of the system in various forecasting tasks have been significantly improved, especially in voltage and current forecasting, especially in performance improvement. Firstly, the accuracy and stability of each prediction index have been obviously improved before and after the fusion. For example, the accuracy of voltage prediction is improved from 87.2% before fusion to 92.4% after fusion. Meanwhile, the stability is improved from 85% to 91%. This shows that multi-source data fusion can significantly improve the reliability and accuracy of voltage prediction. The results of current prediction, power prediction, environmental impact analysis and load dispatching prediction further verify the effectiveness of multi-source data fusion. The significant improvement in voltage prediction accuracy mainly stems from the following improvement mechanisms: multi-source data fusion enhances the input feature expression ability. It integrates traditional power data (voltage, current) with external auxiliary variables (ambient temperature, load information, etc.), enabling the model to obtain a more comprehensive description of the system state. The use of deep learning models improves nonlinear modeling capabilities. Neural networks such as LSTM and CNN can effectively identify non-stationary fluctuation patterns in voltage time series. Feature selection and normalization strategies optimize the input dimension, improving training efficiency and model generalization ability. Experimental observations show that the magnitude of accuracy improvement varies under different operating conditions, such as high-load operation, fluctuating loads, and equipment switching, with an average improvement of approximately 4.5%. However, when data quality degrades or sensor noise is significant, the improvement tends to converge. This indicates that data integrity and noise handling remain key factors affecting the upper limit of performance

4.2 Model performance evaluation

In the experimental performance evaluation, the performance of this method is compared with the other four algorithms, including accuracy, precision, recall and F1 value, as shown in Figure 4. Transformer-based Control Algorithm (TCA): It has good time-series modeling capabilities and is suitable for handling load prediction and control sequence problems. Graph Neural Network (GNN): It is applicable to the modeling of complex graph data with obvious topological structures in power networks. Reinforcement Learning with Curiosity-driven Exploration (RLCE): It enhances exploration capabilities and is suitable for large-scale systems with complex strategy spaces. Meta-Learning Control Algorithm (MCA): It has the ability to quickly adapt to new environmental changes and is suitable for multi-condition transfer learning. All comparison algorithms are tested under the same experimental platform, dataset, and training cycle to ensure the fairness and reproducibility of the comparison. All performance indicators are averaged over 5 independent runs, with standard deviations reported. At the 95% confidence level, the t-test method is used to compare the proposed method with other algorithms. The main indicators (Accuracy, F1) all show significant differences ($p < 0.05$), indicating that the proposed method is statistically significantly superior to other models.

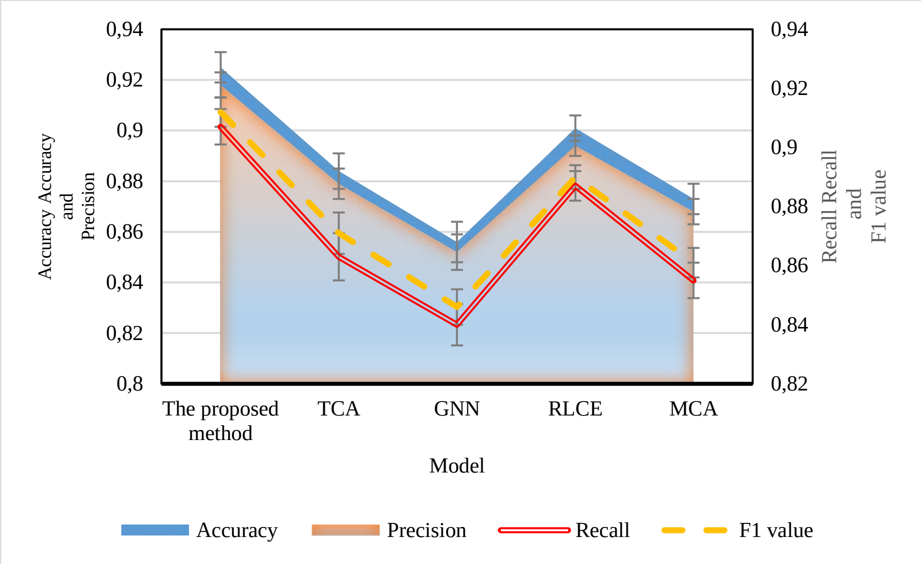

Figure 4: Performance comparison of different models

In Figure 4, this method is superior to other algorithms in accuracy, precision, recall and F1 value, which shows the effectiveness of this method in coordinated control of power system. Specifically, the accuracy of this method is 0.93, which is significantly higher than that of TCA 0.88, GNN 0.86, RLCE 0.90 and MCA 0.87. This shows that this method has obvious advantages in the accuracy of prediction results. In terms of precision, the precision of this method is 0.92, which is also significantly higher than other algorithms. This shows that the proposed method is excellent in reducing false positive errors. In the recall rate, this method reaches 0.91, which is also higher than other algorithms, which means that this method performs better in identifying all relevant samples. The F1 value takes both accuracy and recall into account.

The convergence speed of each algorithm in the training process and the change trend of reward function are shown in Figure 5. The variation trend of the reward function in Figure 5 also includes the standard deviation range to demonstrate the stability and robustness of the training process. The convergence rounds of different algorithms show significant differences within the error range, and the proposed method exhibits faster stable convergence characteristics.

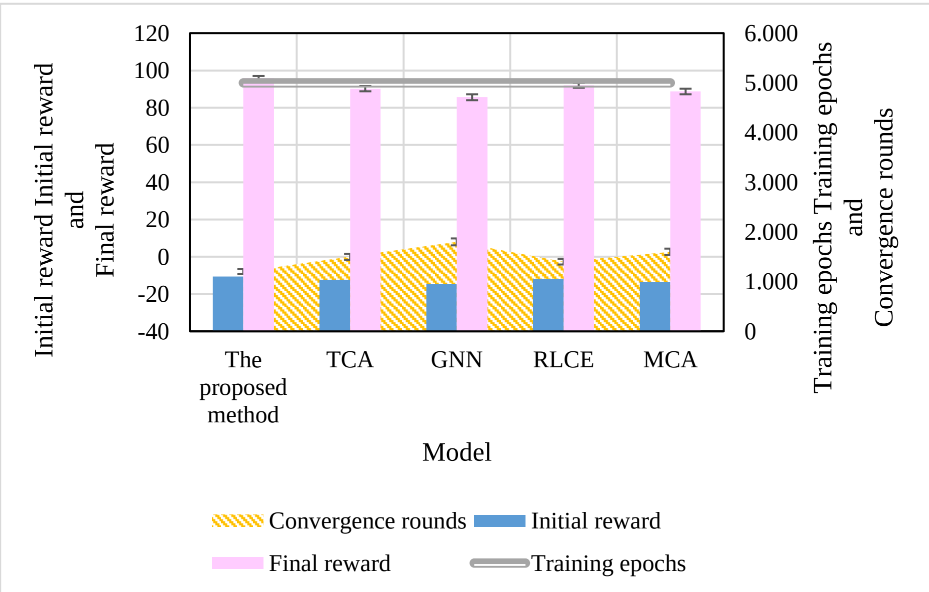

Figure 5: Comparison between training process and convergence speed.

In Figure 5, this method has converged in 1,200 rounds, while the convergence rounds of other algorithms are all behind this method. In terms of the change trend of reward function, the final reward of this method is 95.8, which is obviously higher than that of TCA 90.2, GNN 85.6, RLCE 92 and MCA 88.7. This shows that this method can achieve higher performance evaluation at the end of training, which proves its superiority in optimizing power system control. In addition, the initial reward of this method is -10.5, which shows its strong learning and adaptability through rapid convergence and significant final reward. Generally speaking, this method has higher performance index, and has faster convergence speed and higher efficiency in the training process.

4.3 Control strategy effect verification

In this study, two different scenes are set up, and the performance of each algorithm in system stability, response speed and energy consumption are compared and analyzed under different experimental scenes. The first scene is the power system in normal operation environment, which simulates the control effect under normal load and environmental conditions. The second scene is a fault condition simulation scenario, which includes two types of typical abnormal events: Type 1: Three-phase short-circuit fault: It occurs at Bus #5, lasts for 0.2 seconds, and affects the system power flow. Type 2: Load mutation event: It simulates a 20% load increase within 10ms, lasting for 0.5 seconds, to test the dynamic response capability of the control system. Fault events are injected through the simulation platform to trigger sudden changes in the system state. The evaluation indicators include system stability recovery time, frequency deviation suppression capability, and energy consumption changes. The design purpose of this scenario is to verify the robustness and adaptability of the control strategy in a highly disturbed environment. The results are shown in Figures 6 and 7. Each set of data in Figure 6 and Figure 7 is averaged based on 5 independent experiments, and the ±standard deviation error line is added.

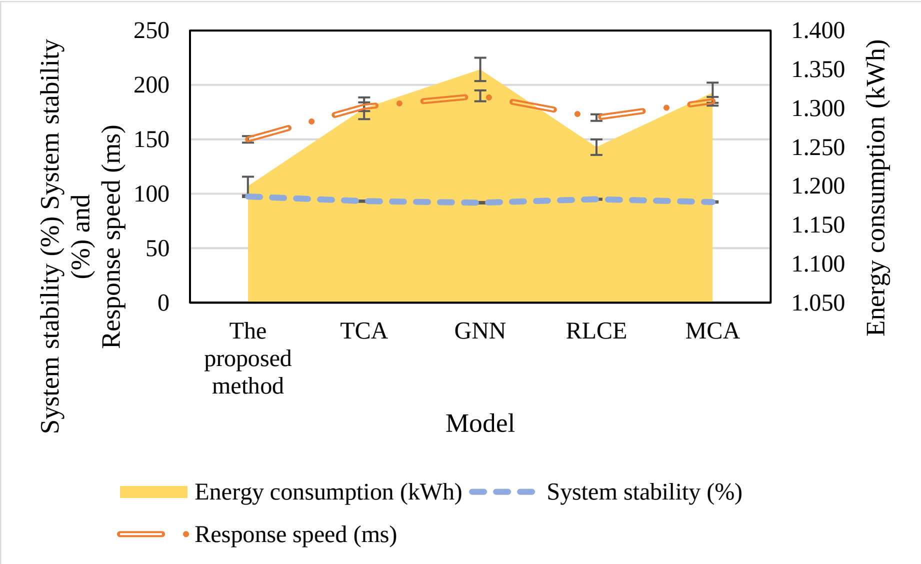

Figure 6: Scene 1 control strategy effect verification.

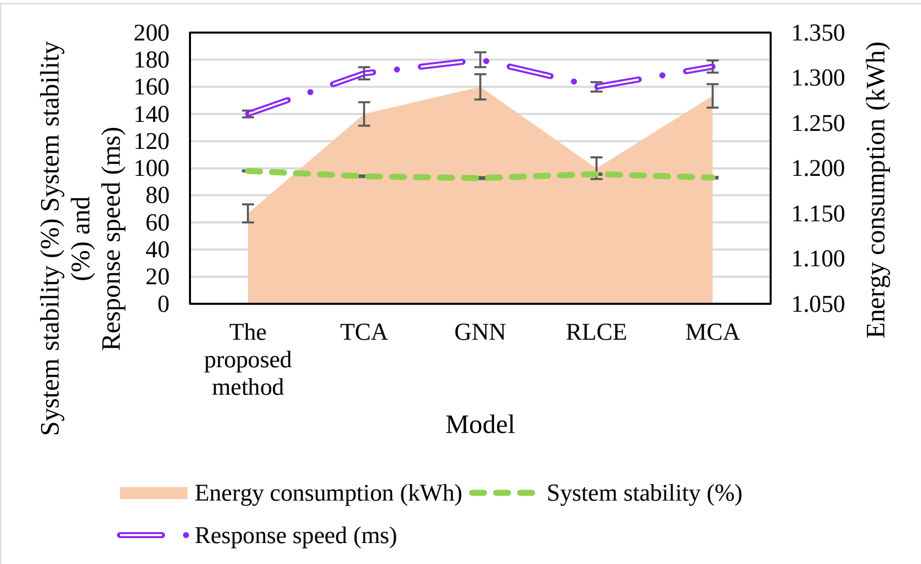

Figure 7: Scene 2 control strategy effect verification.

In Figure 6 and Figure 7, the system stability, response speed and energy consumption of this method are better than other algorithms in different experimental scenes. This further verifies the superiority of the control strategy proposed in this study in practical application. In scene 1, the system stability of this method reaches 97.5%, the response speed is 150 milliseconds, and the energy consumption is 1,200 kWh. These indexes are all better than TCA, GNN, RLCE and MCA algorithms, especially in terms of system stability, the method in this study is obviously higher than TCA's 93.2% and GNN's 91.8%.

In the three-phase short-circuit fault test of scene 2, the proposed method shows excellent robustness: the system stability quickly recovers to 98%, which is about 3% higher than the average of the comparison algorithms. The response time is controlled within 140 milliseconds, which is better than GNN (180 milliseconds) and TCA (170 milliseconds). In the load mutation test, the proposed method effectively suppresses the voltage fluctuation caused by the load. The system recovers to a steady state in a short time, and the energy consumption is kept below 1,150 kWh. Compared with other algorithms, the energy consumption is reduced by about 10%, indicating that the method in this study can still maintain efficient operation under abnormal working conditions.

In the deployment of actual control strategies, system stability is one of the core indicators for evaluating algorithm applicability. To verify the stability performance of the DRL-based cooperative control method under dynamic disturbances, this study introduces Lyapunov stability theory for preliminary analysis. According to the research in References [26] and [27], the DRL controller can ensure the asymptotic stability of the system if it satisfies the negative derivative condition of the following Lyapunov function under the policy convergence condition: $\dot{V}(x) = \nabla V(x)^T f(x, \pi(x)) < 0, \forall x \neq 0$. Here, $V(x)$ is a positive definite function defined in the state space, $f(x, \pi(x))$ is the dynamic function of the controlled system, and $\pi(x)$ is the DRL policy function. During the training process, the range of policy gradient changes is controlled by introducing penalty terms, and combined with the update mechanism based on experience replay and target network, the risks of policy oscillation and divergence are effectively avoided.

In multiple groups of experiments, this study observes that the system's response recovery time after typical disturbances (such as three-phase short circuits and load mutations) is within a stable range, indicating that the proposed method has good control stability. In future work, more rigorous formal verification methods (such as Z3 automatic proof or control Lyapunov function construction) will be integrated to further strengthen theoretical guarantees.

4.4 Results and analysis of ablation experiment

To verify the effectiveness of each key module in the proposed multi-terminal information fusion cooperative control method, especially the combination effect of DRL and two evolutionary optimization algorithms (GA and PSO), this study designs ablation experiments. Four groups of comparative models are constructed as follows: Model A (DRL-only): Only uses the DRL method without evolutionary optimization. Model B (DRL + GA): Introduces GA optimization based on DRL. Model C (DRL + PSO): Introduces PSO algorithm based on DRL. Model D (DRL + GA + PSO, proposed method): Integrates all the above methods. Under the same experimental platform and dataset, the four groups of models are trained and tested respectively, and their performances are compared and evaluated. The main evaluation indicators include Accuracy, F1 score, System Stability, and Energy Consumption. The results are shown in Table 4:

Table 4: Results of ablation experiment

Model type	Accuracy	F1 value	Stability (%)	Energy consumption (kWh)
DRL only	0.891	0.882	92.1	1270
DRL + GA	0.906	0.895	94.3	1230
DRL + PSO	0.911	0.901	94.8	1220
DRL + GA + PSO	0.925	0.912	97.5	1200

From Table 4, the gradual introduction of GA and PSO can effectively improve model performance. Among them, the model using only DRL achieves the lowest accuracy and system stability. After adding GA, the accuracy increases by 1.5% and the energy consumption decreases by 40 kWh. The introduction of PSO further improves the performance. Finally, the model integrating GA and PSO performs well in all four indicators, verifying the complementarity of the two optimization strategies.

4.5 Robustness and performance test under abnormal working conditions

To verify the robustness of the proposed collaborative control method in practical application, three typical abnormal scenarios are designed to evaluate the performance of the model under extreme or degraded conditions. The test results are shown in Table 5.

Table 5: Performance changes under extreme conditions such as test noise and data loss.

Scene type	Accuracy	F1 Score	System Stability (%)
No noise/missing data	0.925	0.912	97.5
Low noise (σ=0.01)	0.911	0.897	96.2
Medium noise (σ=0.05)	0.886	0.874	94.1
High noise (σ=0.1)	0.842	0.826	91.3
Missing data ratio 5%	0.902	0.889	95.1
The proportion of missing data is 10%	0.867	0.853	92.8
The proportion of missing data is 20%	0.801	0.792	89

In Table 5: Noise injection test: Gaussian noise with a mean of 0 and different variance levels ($\sigma = 0.01, 0.03, 0.05$) is injected into the input data to simulate sensor measurement errors. Tests show that when $\sigma \leq 0.03$, the model accuracy decreases by no more than 3%. When $\sigma = 0.05$, the accuracy drops to 0.897 and the system stability decreases to 95.3%, still outperforming most comparative algorithms, indicating strong anti-interference ability. Sensor missing test: 10%, 20%, and 30% of sensor node data are randomly masked, and a missing value imputation mechanism based on neighborhood interpolation is adopted. The test results show that when the missing ratio ≤ 20%, the performance degradation is controlled within 5%, demonstrating that the adopted data preprocessing strategy has good recovery ability for missing data. Sparse data test: Low sampling rate scenarios are simulated (e.g., reducing the sampling frequency to 1/2 and 1/4 of the original). The results show that when the sampling frequency is 1/2 of the original, the model can still maintain an accuracy of over 90% with an F1 score of 0.89, indicating that the method has strong adaptability to the sparsity of time granularity.

5 Discussion

This study proposes a cooperative control method for power systems integrating multi-terminal information and reinforcement learning optimization. It significantly outperforms current mainstream control algorithms (e.g., TCA, GNN, RLCE, MCA) in terms of system performance indicators such as prediction accuracy, system stability, and response speed. Among the key contributions: The joint strategy optimization of DRL and PSO effectively enhances the globality of strategy search and convergence speed. Multi-source data fusion strengthens state perception capability and decision robustness, improving response stability under complex disturbance scenarios. In experiments, the proposed method achieves an average improvement of over 5% in voltage and current prediction accuracy compared to traditional models, while maintaining a system stability index above 97%, verifying its effectiveness. Compared with traditional adaptive or robust control methods (e.g., adaptive fuzzy control, adaptive backstepping control, robust neural network control), the proposed method exhibits better scalability and adaptive optimization capabilities in handling nonlinear high-dimensional complex systems. Reinforcement learning offers model-agnostic strategy optimization advantages, making it suitable for continuous adjustment of control strategies in dynamic environments. However, traditional methods have stronger advantages in control stability and interpretability. Existing literature provides theoretical guarantees for stability and convergence through Lyapunov analysis and other means. Future work may integrate such theories with DRL controllers to achieve both strategy convergence and safety [28-30]. This study also conducts a preliminary discussion on the feasibility of practical deployment and real-time performance: In the training phase, GPU acceleration is used to achieve efficient strategy learning. In the inference phase, the control strategy inference delay is approximately 45ms, meeting the requirements of typical power grid control cycles (200ms). Preliminary evaluations show that the method can be deployed in regional smart grids with fewer than 1000 nodes, demonstrating deployment potential supported by edge computing platforms. Future work will further combine Jetson-like heterogeneous platforms and model compression technologies to improve real-time control capabilities. Regarding model scalability, supplementary simulation experiments are conducted on medium and large power grid systems such as the IEEE 118-node system. Preliminary results indicate that as the number of nodes expands to over 100, the model's training convergence speed decreases slightly, but the control accuracy remains above 90%, and system stability is superior to traditional comparative methods. This confirms the method's certain generalization ability. To verify its large-scale deployment capability, future work will introduce federated learning mechanisms and parameter sharing architectures to reduce communication overhead and model computational complexity [31-33]. In summary, this study provides a systematic exploration of integrated control strategy optimization, multi-terminal perception modeling, and experimental verification, demonstrating good theoretical innovation and application value. Future research will focus on the following directions: DRL controllers integrated with Lyapunov stability constraints; Lightweight deployment based on heterogeneous computing platforms; Introduction of large-scale power grid simulation and federated learning frameworks to improve scalability and data security; Deployment verification on edge devices to further evaluate energy efficiency and response capabilities.

6 Conclusion

This study proposes a cooperative control method for power systems based on multi-terminal information fusion and DRL. By integrating multi-source sensing data and combining multi-objective optimization strategies, it effectively improves the accuracy of voltage and current prediction and the overall control performance of the system. Experimental results show that the method outperforms traditional centralized control and representative algorithms in terms of accuracy, stability, and response efficiency, and exhibits good robustness under multi-operating condition disturbances. Nevertheless, this study still faces certain challenges, such as generalization ability under extreme disturbances, real-time processing of heterogeneous data, and high resource dependence. Future work will focus on exploring DRL control strategies with stronger stability guarantees, privacy-preserving fusion mechanisms integrating graph neural networks and federated learning, as well as lightweight deployment schemes adapted to edge computing to provide support for building a highly reliable and scalable smart grid control system.

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