ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

# Design of regional centralized power generation economic dispatch system based on neural network optimization algorithm

*Qingquan Yan*[1], *Jianxin Zhang*[1,*], *Xiaocui Wu*[1], *Zhiqi Liu*[1], *Tian Zhu*[1] *and Jianhua Xu*[1]

[1] Hubei Energy Group Loushui Hydropower Co., Ltd., Enshi, Hubei, 445000

**SUMMARY:** *In this paper, the economic dispatch system based on neural network optimization algorithm is designed for the cascade hydropower regional centralized power generation scenario. The system integrates the functions of hydrologic monitoring, runoff prediction, medium and long-term optimization scheduling, annual monthly weekly planning, working condition recognition, early warning analysis and feedback writeback, and jointly codes the water level, flow, storage capacity, output, maintenance plan and power grid command of three power stations of Jiangping River, Bashou River and Shuojinshan. And the rolling solution is completed under the constraints of water balance, minimum lower discharge, water level boundary and unit operating conditions. The results show that the average flow prediction error of ten days is 6.8%, the monthly planning deviation is 3.5%, the hydropower utilization rate is 91.8%, and the average scheduling response delay is 1.7 s, which can support plan generation, online correction and closed-loop scheduling execution. At the same time, the system identifies the water state of abundance and dryness according to the frequency threshold of 30% and 70%, and the overall operation is stable, and the plan connection is smooth.*

***KEYWORDS:*** *Regional centralized power generation; Economic dispatch; Neural network optimization; Intelligent scheduling system*

## 1 Introduction

Under the background of the continuous development of new power system construction, regional centralized power generation has changed from single station decentralized control to cross-station, multi-period, and strong constraint collaborative computing. For cascade hydropower stations, the economic dispatch is no longer only based on the experience curve for output allocation, but needs to put the storage flow, water level process, unit state, load demand, maintenance arrangement and power grid command into a unified data space to complete the joint analysis. According to the information provided by users, the regional centralized power generation economic operation and dispatching system takes hydrological monitoring and forecasting data as the center, integrates runoff forecasting, medium and long-term optimal dispatching, and generation planning and reporting into an integrated system. The short-term forecast covers less than three days, and the medium and long-term forecast covers more than three days to less than one year. The research object involves cascade power stations such as Jiangping River, Basjiao River and Suojinshan, and synchronously linked with annual, monthly and weekly plans. This operation pattern shows that the economic dispatch in the regional centralized control scene has been transformed

*18064246026@163.com
https://doi.org/10.65102/is2026546
Published: 30 April, 2026

from the traditional power production management into a computer system task oriented to multi-source acquisition, time series modeling, constraint deduction, result generation and feedback correction. For the direction of intelligent system, machine learning, software and information system, and automation control that Informatica focuses on, the design of regional centralized power generation economic dispatch system based on neural network optimization algorithm not only has clear engineering objects, but also has a clear calculation method.

Focusing on intelligent scheduling and energy management, Guo et al. studied real-time optimal energy management in microgrid under uncertain environment, and found that deep reinforcement learning can enhance real-time decision-making ability [1]. Hu et al. studied the cooperative operation method of microgrid with multiple time scales and pointed out that the continuous control framework was helpful to improve the effect of multi-stage regulation [2]. Goh et al. studied the phased reward function design and found that the reward structure would directly affect the scheduling learning results [3]. Alabdullah et al. studied microgrid energy management based on deep Q-network and verified the feasibility of the learning model in complex constraints [4]. Muriithi et al. studied the optimal energy management of grid-connected optical storage microgrid and showed that deep Q-network has strong expression ability for economic operation [5]. Phan et al. studied intelligent scheduling of islanding microgrid and found that deep network can enhance policy adaptability under complex operating conditions [6]. Ding et al. studied distributed non-convex economic dispatch and proved that multi-agent deep reinforcement learning has strong potential for solving economic dispatch [7]. Han et al. studied the autonomous control technology of optimal active power scheduling and believed that deep reinforcement learning was suitable for dealing with multivariable coupled scheduling tasks [8]. The above research provides a methodological basis for intelligent scheduling, but the system-level organization, plan linkage and online execution expression for cascade hydropower regional centralized control still need to be further refined.

Combined with the existing engineering data, the economic dispatch of regional centralized power generation is divided into five continuous links: prediction, optimization, planning, execution and feedback. At the system level, heterogeneous data such as input water level, storage capacity relationship, downstream water level and flow relationship, installed capacity, non-power generation water, and grid dispatch are uniformly connected. The average flow rate of ten days, adjustable output of units, operating conditions and constraint boundaries are jointly learned, and the calculation results are directly mapped to the generation process of annual, monthly and weekly power generation plans. The working condition recognition scheme in the data also shows that the regional centralized control scene has the foundation of second level acquisition, steady state and transient state division, LSTM transient state recognition, DNN anomaly early warning and rule orchestration, which provides software support for online update, abnormal constraint correction and closed-loop execution of the economic dispatch system. Based on this technical condition, this paper intends to construct a neural network optimal dispatching framework for regional centralized power generation scenarios, so as to form an economic dispatching system design scheme that takes into account computational efficiency, planning accuracy, execution stability and engineering adaptability. At the same time, the working condition portrait proposed by the data is composed of speed, head, flow, output, vibration, swing, upstream water level, downstream water level, water temperature, equipment health status and time series mode, and supports working condition coding, rule configuration, index analysis and history tracing, which makes the scheduling model not only deal with hydrological and load information. It can also obtain more detailed discrimination basis at the unit state level. Therefore, the scheduling results no longer stay at the static plan output, but can enter the continuous correction and state writeback during the operation process, and then form a closed-loop collaboration between the system layer and the algorithm layer, which provides stable support for accurate scheduling.

# 2 Related work

The economic dispatch of power station group under regional centralized control mode has evolved from single output allocation to cross-station cooperative computing tasks. The scheduling result is not only affected by load forecasting, incoming water process and unit state, but also directly related to data collection frequency, state recognition granularity, planning logic and execution writeback mechanism. According to the data provided by users, the economic operation and dispatching system of regional centralized power generation takes hydrological monitoring and forecasting as the center, integrates runoff forecasting, medium and long-term optimal dispatching, generation planning and reporting into an integrated platform, and synchronously integrates modules such as operating condition recognition, DNN early warning, LSTM transient identification and rule engine. This means that the review of related work should not stop at the traditional power dispatch level, but should be carried out in a unified framework of computational model, temporal learning, system linkage and software implementation.

Lin et al. studied the economic dispatch method of microgrid in OPAL-RT environment and found that deep reinforcement learning could improve the real-time performance of dispatch decision in the linkage scenario of simulation and control [9]. Liu et al. studied the real-time economic energy management of microgrid considering uncertainty and found that deep reinforcement learning has good online adaptation ability under dynamic state update [10]. Feng et al. studied the federated deep reinforcement learning framework in the optimal control of multiple virtual power plants and found that the distributed training mechanism was helpful to enhance the robustness of multi-agent collaborative control [11]. Xiao et al. studied the management method of networked multi-energy microgrid and found that improved DQN could improve the scheduling efficiency in complex energy coupling scenarios [12]. Zhang et al. studied the multi-agent deep reinforcement learning strategy for security scheduling in energy hubs and found that multi-agent collaborative modeling can improve the consistency of distributed resource allocation [13]. Abid et al. studied the multi-objective and multi-agent deep reinforcement learning method in microgrid resource planning, and found that multi-objective modeling was helpful to unify the economy and resource allocation effect [14]. To more clearly present the differences in objects, methods, and applicable scenarios of existing studies, the comparison of related technology paths is shown in Table 1.

*Table 1: Comparison of technology paths and applicable characteristics of related studies*

| References | Research Object | Core Method | Main Computational Content | Main Findings | Implications for This Study |
|---|---|---|---|---|---|
| Lin et al. [9] | Microgrid economic dispatch | Deep reinforcement learning | State perception, action generation, and economic dispatch decision-making in the OPAL-RT environment | Deep reinforcement learning can improve the real-time response capability and control stability of the economic dispatch process | Its real-time decision-making modeling idea can be adopted for online dispatch output in regional centralized control scenarios |
| Liu et al. [10] | Real-time energy management of microgrids | Deep reinforcement learning | Dynamic updating of load, energy supply status, and dispatch actions under uncertain conditions | Learning-based dispatch models show good adaptability in operating scenarios with uncertain disturbances | It can support rolling correction and dynamic schedule adjustment in regional centralized power generation |
| Feng et al. [11] | Coordinated control of multiple virtual power plants | Federated deep reinforcement learning | Collaborative training, optimal control, and information sharing in a multi-agent distributed structure | The distributed training mechanism helps enhance the robustness of multi-station coordinated control | It can provide a reference for cross-station coordination and data sharing in regional centralized control of multiple power stations |
| Xiao et al. [12] | Networked multi-energy microgrids | Improved DQN | State modeling, action selection, and energy management optimization for networked energy units | Improved DQN can enhance dispatch efficiency in complex coupled energy systems | Its multivariable state encoding approach can be adopted for feature construction in regional centralized economic dispatch |
| Gao et al. [15] | Economic dispatch of virtual power plants | GRU-PPO | Joint use of temporal state representation and policy optimization for solving economic dispatch problems | Temporal neural networks help strengthen the modeling capability of dynamic operating processes | It can provide methodological support for the joint modeling of inflow processes, load variation, and unit status |
| Wang et al. [16] | Look-ahead economic dispatch | Deep reinforcement learning | Multi-stage economic dispatch decision-making based on rolling forecasting | The look-ahead mechanism can improve dispatch feasibility under multi-period coupled constraints | It can be used in the multi-time-scale dispatch design linking annual, monthly, and weekly plans in this study |

It can be seen from Table 1 that the existing research has formed a clear technical path in real-time decision-making, distributed collaboration, time series modeling and multi-stage optimization. However, most of the work still focuses on microgrid, virtual power plant or multi-energy system, and focuses on policy learning and scheduling solution itself. In contrast, the economic dispatch of regional centralized power generation is faced with longer business chain and more complex software organization form. It not only requires the algorithm to give a feasible output scheme, but also requires the results to be embedded in the continuous process of prediction, planning, execution and writeback. Therefore, the comparison of related work should not only stop at the control strategy level, but also pay attention to the connection between the output of the model and the function of the scheduling system.

Gao et al. studied the economic dispatch method of virtual power plant based on GRU and PPO, and found that the gated timing structure can enhance the expression ability of the dynamic dispatch process [15]. Wang et al. studied the adaptive forward-looking economic dispatch method and found that deep reinforcement learning is more suitable for dealing with multi-stage coupling constraints in the rolling decision-making process [16]. Yu et al. studied the application of improved soft actor critic algorithm in energy optimization of microgrid and found that continuous action space learning can enhance the smoothness of scheduling output [17]. Ding et al. studied the distributed energy management method of multi-regional integrated energy system and found that multi-agent deep reinforcement learning is more suitable for multi-regional collaborative scenarios [18]. Duran et al. studied the optimal scheduling method of microgrid based on prediction and found that the linkage of prediction results and scheduling decisions can improve the plan executability [19]. Hu et al. studied the method of retired power batteries participating in the scheduling of integrated energy systems, and found that deep reinforcement learning was suitable for dealing with complex timing control with the participation of energy storage [20].

The above researches provide a solid algorithm foundation for intelligent dispatching. However, from the perspective of the engineering structure of regional centralized power generation, most of the existing results focus on microgrid, virtual power plant or integrated energy system, and the research focus mainly falls on the level of action decision-making, strategy learning and resource coordination. In contrast, the cascade hydropower regional centralized control scenario has stronger business chain characteristics. The relevant scheme in the user profile shows that the system should not only complete the prediction of ten-day average flow, annual average flow and short-term storage flow, but also further generate annual, monthly and weekly power generation plans by combining the water level and storage capacity relationship, downstream water level and flow relationship, installed capacity, non-power generation water consumption and grid dispatch requirements of Jiangping River, Bashou River and Suojinshan power stations. And retain parameter adjustment, plan reporting and ledger tracking capabilities. This indicates that the related work of regional centralized power generation economic dispatch should cover the three levels of forecasting model, optimization model and planning system at the same time, instead of only discussing the single dispatch solution.

In terms of the state analysis of hydropower equipment, the user document gives another technical clue closely related to economic dispatch, namely condition identification and early warning feedback. The data show that the condition recognition has formed a multi-source profile structure of "physics-environments-health-business", which can not only deal with steady-state conditions by SVM and RF, but also deal with transient processes such as starting and stopping, increasing and reducing load by LSTM. In addition, online early warning is realized by DNN anomaly recognition, second level acquisition and rule engine. For the regional centralized power generation system, the value of this kind of research is not only reflected in the operation and maintenance monitoring layer, but also reflected in the scheduling constraint update layer. Whether the unit is in the grid-connected state, the load increase process after grid-connected, the stable operation state or the load reduction process will directly affect the adjustable output boundary, the plan correction rhythm and the command issuing strategy. Therefore, studies on neural networks in related work cannot be evaluated only by prediction accuracy or reward convergence, but also need to form computable connections with scheduling business logic, plan generation processes, and execution feedback mechanisms.

In summary, the existing research has accumulated rich results in deep reinforcement learning, temporal neural network, multi-agent cooperation and prediction-driven dispatching, and also provides a method reserve for regional centralized power generation economic dispatching. However, for the regional centralized control system of cascade hydropower joint operation, the related work still needs to be further focused on the integration direction of "prediction-optimization-plan-execution-feedback". Based on this understanding, this paper puts the neural network optimization algorithm and the overall architecture of the regional centralized power generation system in the same design link in the subsequent research, so that the economic dispatch is no longer just the algorithm output result, but a systematic calculation function that can enter the planning, operation correction and state writeback process, and improves the engineering adaptability of the regional centralized control scene.

# 3 Methods and materials

## 3.1 Neural network optimization algorithm for regional centralized power generation economic dispatch

The economic dispatching of power generation in regional centralized control scenario is no longer the static output allocation of a single power station, but the incoming water process, reservoir water level change, unit operating condition, load demand, grid command and planning boundary of cascade power stations are put into the same calculation link for joint solution. Combined with the business structure of "runoff prediction, medium and long term optimal dispatching, generation planning and reporting" in regional centralized power generation economic operation dispatch system, the neural network optimization algorithm is designed as a continuous calculation process of "state encoding, time series prediction, stage solving, condition correction, plan writing back". So that the prediction results can directly enter the regional centralized power generation planning and scheduling execution link.

In order to keep the stage decision consistent with the operation state of regional centralized control, this paper expresses the optimal scheduling objective of the current period as the maximum value of the sum of immediate revenue and subsequent cumulative revenue, and its expression is as follows:

$$B_t^*(Z_t) = \max\{B_t(Z_t, Q_t, \lambda_t) + B_{t+1}^*(Z_{t+1})\} \tag{1}$$

Here, $B_t^*(Z_t)$ represents the maximum cumulative revenue that can be obtained at stage $t$ and state $Z_t$. $B_t$ $Z_t, Q_t, \lambda_t)$ represents the immediate payoff in the current period; Qt represents the storage flow or available water at this stage; Let $\lambda_t$ denote the scheduling decision variables in this phase; $B_{t+1}^*(Z_{t+1})$ denotes the optimal cumulative payoff in the next period. Equation (1) is used to link the current scheduling results with the income of the subsequent stage, so that the economic scheduling can simultaneously take into account the connection between the current execution effect and the subsequent plan.

In the algorithm structure, multi-source monitoring data is first organized as a unified state input, and then nonlinear mapping and trend extraction are completed by neural network, and then the economic dispatch solution is completed by multi-stage recurrence mechanism. Fig.

1 shows the multi-stage recursive solution structure for regional centralized power generation economic dispatch. The core idea reflected in this figure is that the scheduling decision of the current stage not only affects the current revenue, but also changes the state boundary of the next stage. Therefore, it is necessary to unify the current revenue and the cumulative revenue of the subsequent stages for rolling optimization.

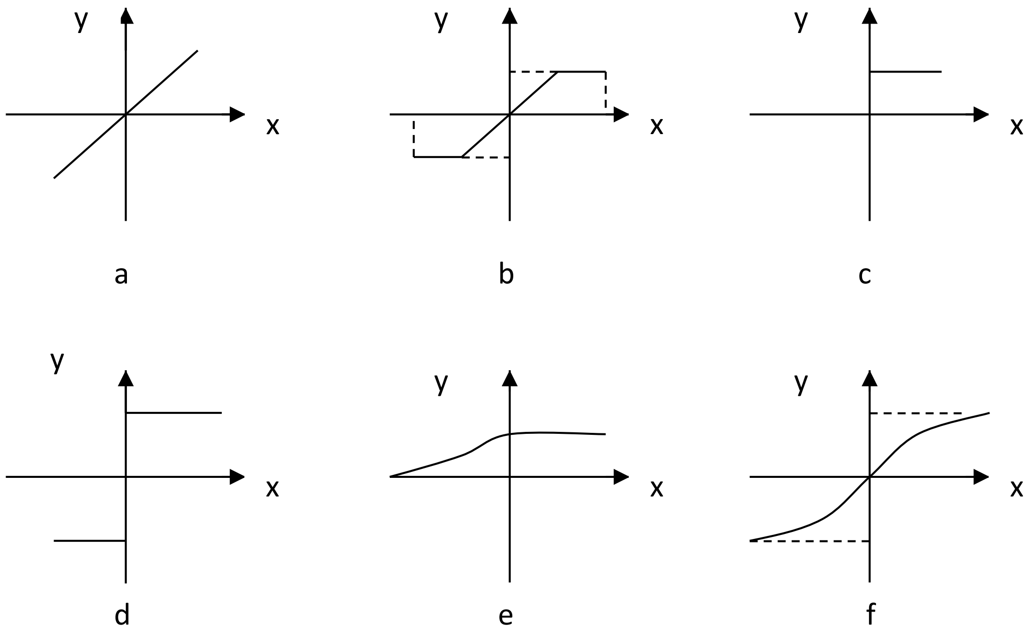


*Figure 1: Multi-stage recursive solution structure for regional centralized power generation economic dispatch*

In the multi-stage recursive framework, it is also necessary to compress the hydrological, load, working condition and planning information into a unified state vector, so that the neural network can complete learning and reasoning in the same feature space, which is defined as follows.

$$s_t = [q_t, h_t, p_t, l_t, r_t, c_t] \tag{2}$$

where $s_t$ denotes the integrated state at time $t$; $q_t$ represents the incoming traffic vector; $h_t$ represents the water level of each reservoir; $p_t$ represents the current output of the unit; $l_t$ represents the system load demand; $r_t$ represents the recognition results of operating conditions. $c_t$ stands for Plan with Constraint encoding. Equation (2) converts the heterogeneous information scattered in hydrological monitoring, condition identification and plan management into a unified input, which provides a data basis for subsequent neural network prediction.

After the state vector is formed, it is necessary to establish the joint prediction mapping relationship between incoming water and adjustable output power in the next period, so that the scheduling model has the forward-looking computing ability. The form is written as follows.

$$\hat{y}_{t+1} = f_\theta(s_t, x_t) \tag{3}$$

where $\hat{y}_{t+1}$ represents the forecast output in the next period; $f_\theta$ denotes the neural network mapping with parameters $\theta$. $x_t$ represents exogenous inputs, including meteorological information, grid commands, and overhaul plans. Equation (3) is used to describe the nonlinear relationship between incoming water change, output boundary and external scheduling demand, so that short-term forecasting and medium-and long-term planning can be processed jointly in the same solution process.

After the prediction results enter the dispatch layer, the regional centralized power generation needs to integrate generation revenue, operation cost and planning deviation into the objective function, and form a comprehensive benefit expression suitable for cascade scenarios, which is in the following form:

$$J = \sum_{t=1}^{T} ( R_t - C_t - \lambda_1 U_t - \lambda_2 D_t) \tag{4}$$

where $J$ represents the total benefit of the scheduling period;$R_t$ represents the revenue of power generation; $C_t$ represents the operating cost; $U_t$ stands for abandoned water loss; $D_t$ stands for plan deviation penalty. $\lambda_1$ and $\lambda_2$ are the weight coefficients. Equation (4) is used to balance economic benefits, water energy utilization efficiency and consistency of plan execution, so that the scheduling result is not only economical, but also can keep the planned output stable.

After the objective function is determined, the cascade hydropower scheduling still needs to satisfy the basic water conservation relation, so the reservoir water balance constitutes the core physical constraint of the algorithm, and its expression is as follows:

$$V_{i,t+1} = V_{i,t} + Q_{i,t} - G_{i,t} - S_{i,t} \tag{5}$$

where $V_{i,t+1}$ denotes the capacity of the $i$ reservoir at time $t$; $Q_{i,t}$ denotes the inbound flow; $G_{i,t}$ denotes the water consumption for power generation; $S_{i,t}$ denotes the amount of discarded water. Equation (5) is used to ensure that the scheduling action satisfies the hydrological operation boundary, so that the results generated by the neural network will not deviate from the actual reservoir scheduling rules.

In order to ensure that the scheduling results can be directly sent to the centralized control executive end, it is also necessary to constrain the adjustable output range of the unit, and to include the hydraulic head and working condition state into the output boundary at the same time. The relationship is as follows:

$$P_{i,t}^{min} \le P_{i,t} \le P_{i,t}^{max}(H_{i,t}, R_{i,t}) \tag{6}$$

where $P_{i,t}$ denotes the output of the $i$ unit at time $t$; $P_{i,t}^{min}$ and $P_{i,t}^{max}$ denote the minimum and maximum allowable output, respectively. $H_{i,t}$ stands for water purification head; $R_{i,t}$ denotes the current condition category. Equation (6) is used to introduce the head condition and condition identification results into the scheduling boundary at the same time to avoid the generation of out-of-limit instructions in the process of load increase, stable operation or load reduction after grid connection.

Considering that there are many kinds of working conditions in the regional centralized control operation of the unit, such as grid-connected state, load increasing process, stable operation state and load reducing process, this paper further introduces the working condition correction coefficient to make the scheduling action have flexible constraint ability, which is expressed as follows:

$$\alpha_t = \sigma(Wr_t + b) \tag{7}$$

Here, $\alpha_t$ represents the condition correction coefficient; $\sigma$ is the Sigmoid activation function. $W$ and $b$ denote the weight matrix and bias term, respectively. $r_t$ represents the operating condition feature vector. Equation (7) is used to dynamically modify the scheduling action according to the current working condition, so that the algorithm can still maintain stable output under the condition of transient disturbance and abnormal early warning.

Fig. 2 depicts the linkage process in which the condition identification information participates in the modification of the scheduling strategy. The steady-state identification results are used to update the upper and lower limits of the unit output and the operating interval, the transient identification results are used to modify the action step length and the timing adjustment amplitude, and the abnormal identification results are triggered by the early warning rules to reset the constraints and log recording. Therefore, the working condition data is included in the input of scheduling decision, and the output of the neural network is no longer the static solution results from the operation site, but the dynamic scheduling instructions that can be online corrected according to the real-time state changes.

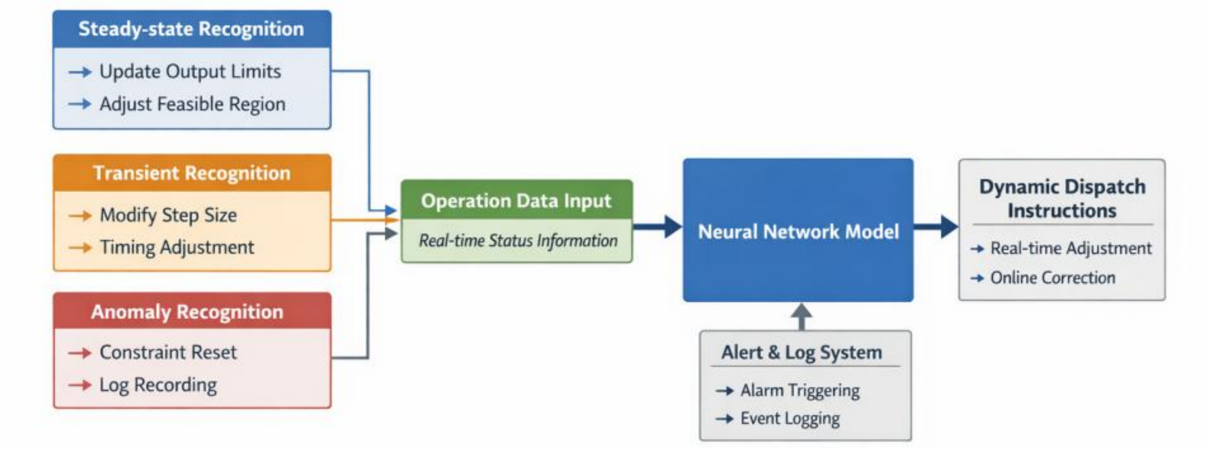


*Figure 2: Scheduling policy modification mechanism driven by condition identification*

After obtaining the correction coefficient, the final scheduling order is determined by the prediction result, the economic target and the feedback of the working condition, and its calculation form is as follows:

$$a_t = \alpha_t \odot \pi_\phi(\hat{y}_{t+1}, s_t) \tag{8}$$

Here, $a_t$ denotes the final scheduling action at time $t$. Let $\pi_\phi$ denote the policy network with parameter $\phi$. $\odot$ represents element-wise weighting operation; $\hat{y}_{t+1}$ and $s_t$ denote the predicted output and the current state, respectively. Equation (8) is used to generate scheduling instructions that can directly enter the steps of planning, scheduling issuance and state writeback, so as to realize the continuous connection between prediction, solving and execution.

Based on the above algorithm structure, the economic dispatch of regional centralized power generation forms a continuous computing link consisting of state perception, time series prediction, stage recurrence, condition correction and command output. The link can integrate ten-day average flow, short-term storage flow, water level and storage capacity relationship, adjustable output of units, working condition recognition results and grid dispatching requirements into the same optimization process, so that the dispatching results are economical, executable and stable. Compared with the static plan-driven single solution method, this neural network optimization algorithm can continuously take in new hydrological data, load changes and equipment status information in the rolling calculation, and adjust the generation plan boundary and unit output allocation accordingly, so that the algorithm output can directly enter the planning, scheduling execution, state writing and log retention process of the regional centralized control system. It provides a unified data basis and computing support for the overall architecture design and implementation verification of the subsequent system.

## 3.2 Overall architecture and functional design of regional centralized power generation economic dispatch system

The economic dispatching system of regional centralized power generation needs to deal with hydrological monitoring, runoff forecasting, medium and long-term optimal dispatching, generation planning, plan reporting and condition warning at the same time. Therefore, the overall design cannot stay in a single model calling layer, and should form a unified software link covering data access, characteristic governance, dispatching solution, planning and feedback writeback. Combined with the business arrangement in the document, this paper divides the system into four parts: data access layer, computing service layer, planning layer and feedback governance layer. The data access layer is responsible for collecting the reservoir characteristic water level, storage capacity relationship, downstream water level flow relationship, discharge curve, installed capacity, non-power generation water, grid scheduling information and real-time measurement points. The computing service layer calls neural network optimization algorithm to complete runoff prediction, working condition identification and economic dispatch solution. The planning layer generates annual, monthly and weekly plans; The feedback governance layer undertakes the functions of early warning push, ledger record and rule writeback. The overall system structure is shown in Fig. 3.

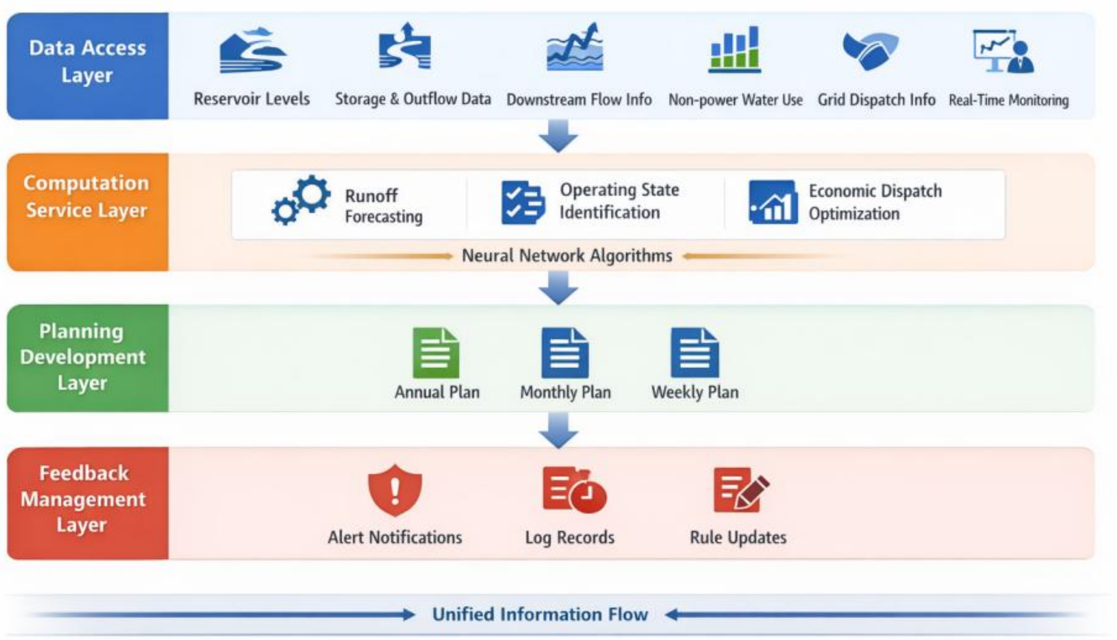


*Figure 3: The overall architecture of the regional centralized power generation economic dispatch system*

In order to allow data from different sources to enter the same computing space, the system needs to unify and fuse the hydrologic, load, unit condition and planning parameters, and form a feature representation that can be directly invoked by the scheduling engine. The expression is as follows:

$$F_t = \phi\left(W_h H_t + W_q Q_t + W_l L_t + W_p P_t + W_m M_t + W_g G_t + b_f\right) \tag{9}$$

where $F_t$ represents the fused feature vector at time $t$. Let $\phi(\cdot)$ denote the nonlinear mapping function; $H_t$ represents water level and storage capacity information; $Q_t$ represents the inbound flow and the outbound flow; $L_t$ stands for load demand; $P_t$ represents the current output of the unit and the grid command; $M_t$ represents the plan parameters and maintenance information. $G_t$ represents the recognition result of working condition; $W_h$,$W_q$,$W_l$,$W_p$,$W_m$,$W_g$ are the weight matrices corresponding to each type of input; $b_f$ is the bias term. Equation (9) is used to compress heterogeneous data scattered in hydrological monitoring, production planning and condition analysis in documents into the same feature space, providing a unified data base for subsequent prediction, optimization and planning.

After the unified feature representation is completed, the functional boundaries and data flow of each layer in the system need to be kept clear to avoid breaking points in planning, scheduling execution and exception writeback. Table 2 shows the module division of the regional centralized power generation economic dispatch system and its corresponding output.

*Table 2: Module division of regional centralized power generation economic dispatch system*

| Layer | Core Functions | Main Data Objects | Output Results |
|---|---|---|---|
| Data Access Layer | Acquisition, cleansing, and standardized encoding | Water level, flow, load, maintenance, monitoring points, and ledgers | Standardized input set |
| Computing Service Layer | Runoff forecasting, operating condition identification, and economic dispatch solving | Fused features, constraint parameters, and operating condition labels | Dispatch solutions, boundary values, and forecasting results |
| Planning Layer | Generation and export of annual, monthly, and weekly plans | Dispatch results, end-of-month water level, and estimated spilled water volume | Planning reports and submission files |
| Feedback Governance Layer | Abnormal warning, rule orchestration, and log and ledger write-back | Warning events, adjustment records, and approval information | Feedback logs and traceability records |

The monthly plan is a further modification on the basis of the annual plan, so the system needs to include the annual plan base, the average flow forecast of the next month, the target water level at the end of the planning month and the expected abandonment water in the calculation of the monthly plan. The generation relationship of the monthly plan can be written as follows:

$$P_{i,t}^{m} = \rho_1 P_{i,t}^{y} + \rho_2 \widehat{Q}_t^{m} + \rho_3\left(H_{i,t}^{tar} - H_{i,t-1}^{act}\right) - \rho_4 S_{i,t}^{ab} \tag{10}$$

Here, $P_{i,t}^{m}$ denote the monthly generation schedule value of the $i$ power station in the scheduled month period $t$. $P_{i,t}^{y}$ denotes the base value given by the annual plan; $\widehat{Q}_{t}^{m}$ represents the average traffic forecast value for the next month. $H_{i,t}^{tar}$ represents the water level at the end of the target month; $H_{i,t-1}^{act}$ denotes the actual water level at the end of the current month; $S_{i,t}^{ab}$ indicates the expected amount of abandoned water; $\rho_1$ to $\rho_4$ are the regulation coefficients. Equation (10) corresponds to the business process in the document "set the expected amount of abandoned water in the planned month, predict the average flow in the next month, input the actual water level at the end of the current month, automatically extract the water level at the end of the next month and calculate the cascade total power generation", so that the generation logic of the monthly plan can form a computable expression in the system.

The weekly plan is refined on a rolling weekly basis on the basis of the medium and long-term scheduling scheme, so the system also needs to synchronously incorporate the predicted runoff, the adjustable output of the unit, the flood control constraint and the maintenance arrangement into the weekly plan calculation, and its expression is as follows:

$$P_{i,d}^{w} = \min\left\{P_{i,d}^{max}, \max\left[P_{i,d}^{min},\ P_{i,d}^{m} + \kappa_1 \hat{q}_{i,d} - \kappa_2 R_{i,d} - \kappa_3 M_{i,d}\right]\right\} \tag{11}$$

Here, $P_{i,d}^{w}$ denote the pre-planned output of the $i$ power station on day $d$ of the weekly plan; $P_{i,d}^{max}$ and $P_{i,d}^{min}$ denote the maximum and minimum adjustable output force, respectively. $P_{i,d}^{m}$ represent the monthly plan decomposition value; $\hat{q}_{i,d}$ denotes the predicted runoff; $R_{i,d}$ represent constraint factors such as water level, flood control and comprehensive utilization. $M_{i,d}$ denotes the maintenance plan impact quantity; $\kappa_1$, $\kappa_2$ and $\kappa_3$ are the regulation coefficients. Equation (11) is used to transform the business requirements of "taking weekly cycle and daily calculation period as the document, comprehensively considering water balance, flood control, power station output, comprehensive utilization, reservoir level and maintenance plan" into the daily scale plan calculation method inside the system.

After the plan is generated, the system should continuously revise the plan status according to the actual execution results to ensure the consistency between the issued plan, the execution results and the reported data. Considering that the power generation plan account management is specially set up in the document, recording the values before and after adjustment, the reasons for adjustment, the adjustment category, the adjustment time and the adjustment person, this paper writes the system rolling correction process as follows.

$$Y_{t+1} = Y_t + \eta_1\left(P_t^{act} - \widehat{P}_t\right) + \eta_2\left(H_t^{act} - H_t^{tar}\right) + \eta_3\left(Q_t^{act} - \widehat{Q}_t\right) \tag{12}$$

where $Y_t$ represents the current plan state; $Y_{t+1}$ represents the modified plan state; $P_t^{act}$ and $\widehat{P}_t$ denote the actual execution output and the model suggested output, respectively. $H_t^{act}$ and $H_t^{tar}$ represent the actual and target water levels, respectively. $Q_t^{act}$ and $\widehat{Q}_t$ represent actual and predicted incoming water, respectively. $\eta_1$, $\eta_2$ and $\eta_3$ are the modified weights. Equation (12) is used to write the execution deviation, water level deviation and incoming water deviation into the rolling correction link uniformly, so as to form a traceable and writable continuous relationship among the annual, monthly and weekly plans.

The system should not only complete the plan calculation, but also trigger the warning and rule response in the abnormal state. It is clearly written in the document that the DNN anomaly recognition model will compare the index data with the normal threshold in real time, trigger an early warning after exceeding the threshold, and the rule engine will perform response actions according to the monitoring scene, and support dynamic adjustment of the threshold and event traceback. Based on this mechanism, early warning feedback strength is defined as follows.

$$\beta_t = \frac{\omega_1 A_t + \omega_2 V_t + \omega_3 C_t}{1 + \omega_4 \Delta_t} \tag{13}$$

Here, $\beta_t$ represents the feedback response strength; $A_t$ indicates the degree of abnormality score. $V_t$ represents the fluctuation amplitude of the index; $C_t$ represents the correlation degree of similar historical events. $\Delta_t$ represents the current scheduling deviation; $\omega_1$ to $\omega_4$ are the weight parameters. Equation (13) is used to control the response priority after the warning results enter the feedback governance layer, so that the exception event processing, constraint tightening, rule triggering and log writeback can be completed in the same closed loop.

Based on the above design, the regional centralized power generation economic dispatch system forms a continuous software link from data access, feature fusion, plan preparation to early warning writeback. The link can integrate the short-term and long-term runoff prediction, monthly and weekly planning, power generation plan reporting, account management and condition early warning analysis proposed in the document into the same platform, and form an interface correspondence with the neural network optimization algorithm mentioned above. In this way, the relationship between the system layer and the algorithm layer is no longer loose splicing, but forms a sustainable update regional centralized control scheduling architecture through unified features, rolling correction and feedback governance, which provides a clear structural basis for subsequent system verification and operation effect analysis.

# 4 Results

## 4.1 Analysis of economic dispatch results of regional centralized power generation

In order to verify the applicability of the regional centralized power generation economic dispatch method in the actual business link, this paper takes three power stations of Jiangping River, Bashou River and Suojinshan as objects, and organizes the experiment according to the process of "runoff prediction -- medium and long-term optimal dispatch -- annual, monthly and weekly plan preparation -- plan reporting and ledger management" in the document. The proposed neural network optimization scheduling method is compared with the rule-driven planning method and the static optimization method. The three groups of methods operate under the same basic data, constraint boundaries and planning period conditions, and the input information includes the average flow of ten days, short-term storage flow, water level and storage capacity relationship, downstream water level and flow relationship, unit maintenance plan, non-power generation water consumption and grid scheduling instructions, so as to ensure that the difference mainly comes from the scheduling mechanism itself, rather than external data diameter changes.

As shown in Fig. 4, within the 3-day short-term prediction window, the proposed method fits the ten-day average flow process more smoothly. The average relative errors of the three power stations of Jiangping River, Basjiao River and Suojinshan are controlled at 6.4%, 6.8% and 7.2%, respectively, and the comprehensive error is 6.8%, which is significantly lower than 10.6% of the rule-driven method and 8.1% of the static optimization method. At the inflection point from high water to flat water, the maximum flow deviation of the proposed method is kept within 4.3 m³/s, while that of the rule-driven method is 7.6 m³/s. This result shows that after the prediction module enters the scheduling link, it can absorb the incoming water change information earlier and provide stable input for the subsequent monthly and weekly plan correction.

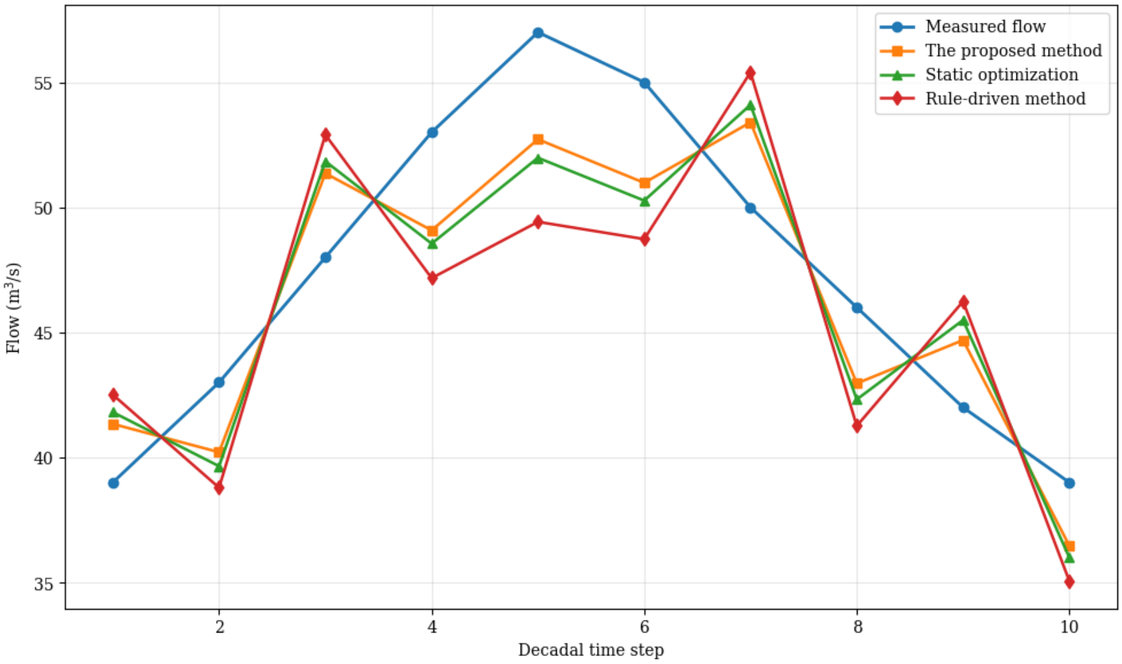


*Figure 4: Comparison between the predicted results of ten-day average traffic and the measured process*

From the overall results, all three plants show good plan consistency and execution stability under the unified scheduling framework. Table 3 shows the comparison results of different methods on key indicators. It can be seen that the proposed method is superior to the other two methods in the five indicators of ten-day average flow prediction error, monthly planning deviation, hydropower utilization rate, abandonment rate and scheduling response delay. The overall monthly planning deviation is controlled within 3.5%, the comprehensive hydropower utilization rate reaches 91.8%, and the average scheduling response delay is compressed to 1.7 s. Compared with the rule-driven planning method, the main advantage of the proposed method is not the local improvement of a single index, but the continuous data transmission relationship between forecasting, scheduling and planning is formed, so that a good connection between multiple planning levels is maintained.

*Table 3: Summary of regional centralized power generation economic dispatch results*

| Method | Ten-Day Average Flow Forecast Error / % | Monthly Scheduling Deviation / % | Hydropower Utilization Rate / % | Water Spillage Rate / % | Dispatch Response Delay / s |
|---|---|---|---|---|---|
| Rule-Based Planning Method | 10.6 | 6.8 | 84.7 | 6.2 | 2.6 |
| Static Optimization Method | 8.1 | 4.9 | 88.9 | 4.1 | 2.1 |
| Proposed Method | 6.8 | 3.5 | 91.8 | 2.7 | 1.7 |

In addition, the proposed method also maintains good adaptability in the stratification results of incoming water state. In the document, 30% and 70% frequency thresholds are used to divide the annual average flow of storage into rich and dry states, and two flow boundaries of 52.0 m³/s and 36.6 m³/s are given. Based on this criterion, Fig. 5 compares the variation of total cascade power generation and water abandonment rate under different inflow states. Under the condition of abundant water, the total cascade power generation of the proposed method reaches 1.284 million kWh, and the water abandonment rate is 3.1%. The total power generation is 1.146 million kWh, and the water abandonment rate is 2.4%. The total power generation in the dry water state is still maintained at 968,000 kWh, and the water abandonment rate is reduced to 1.6%. Compared with the rule-driven method, the total power generation of flat water and dry water stages is increased by 4.7% and 6.2%, respectively, indicating that the rolling correction is more fully adapted to the cross-state switching.

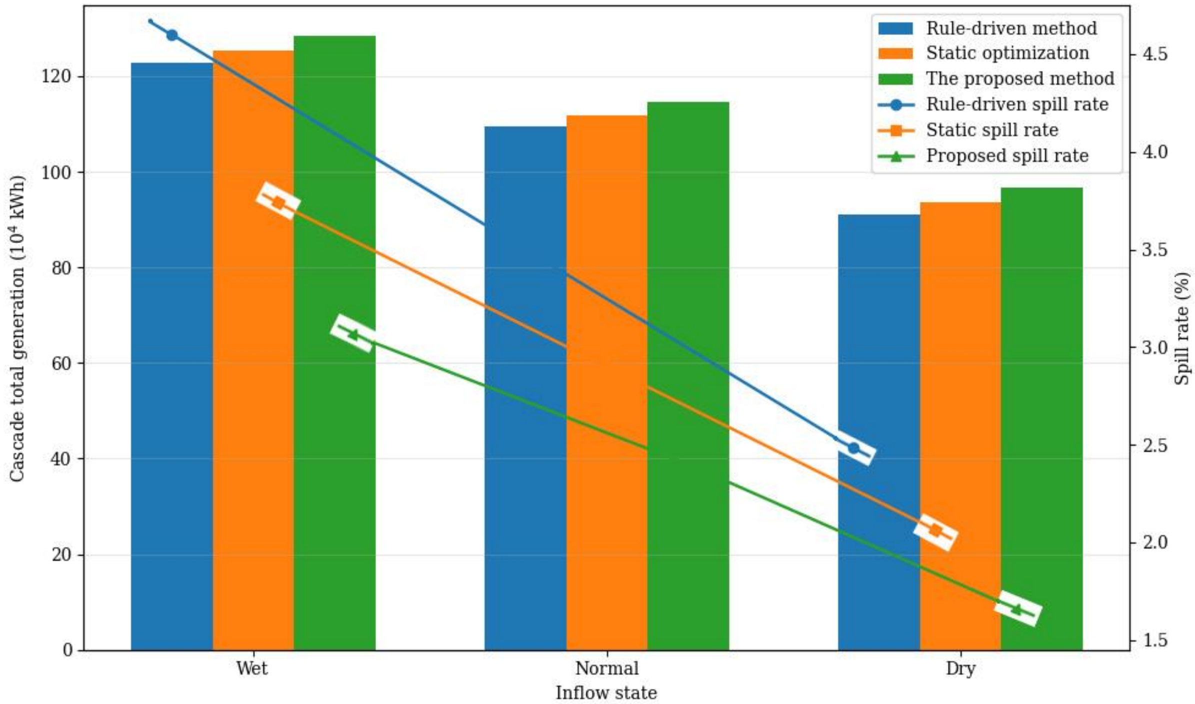


*Figure 5: Variation of cascade total power generation and water abandonment rate under different inflow states*

In terms of planning results, the advantage of the proposed method is mainly reflected in the connection accuracy between monthly and weekly plans. The document clearly proposed that the monthly power generation plan should be further revised and refined on the basis of the annual plan, and the cascade total power generation of the next month and the maximum and minimum adjustable output of each power station should be automatically generated after inputting the actual water level at the end of the month, predicting the average flow of the next month, and setting the expected abandonment water. On the basis of the medium and long term generation dispatch scheme, the weekly plan needs to be decomposed according to the cycle of the week and the calculation period of the day. Fig. 6 illustrates the deviation variation between the monthly planning output and the actual execution results for the three methods. The average deviation of the rule-driven method is 6.8%, and the maximum deviation is 8.1%. The average deviation of static optimization method is 4.9%. The proposed method compresses the average deviation to 3.5%, and the deviation band mainly distributes between 2.7% and 4.1%, which indicates that the plan output can converge synchronously with the execution state, rather than repairing centrally at the end of the month.

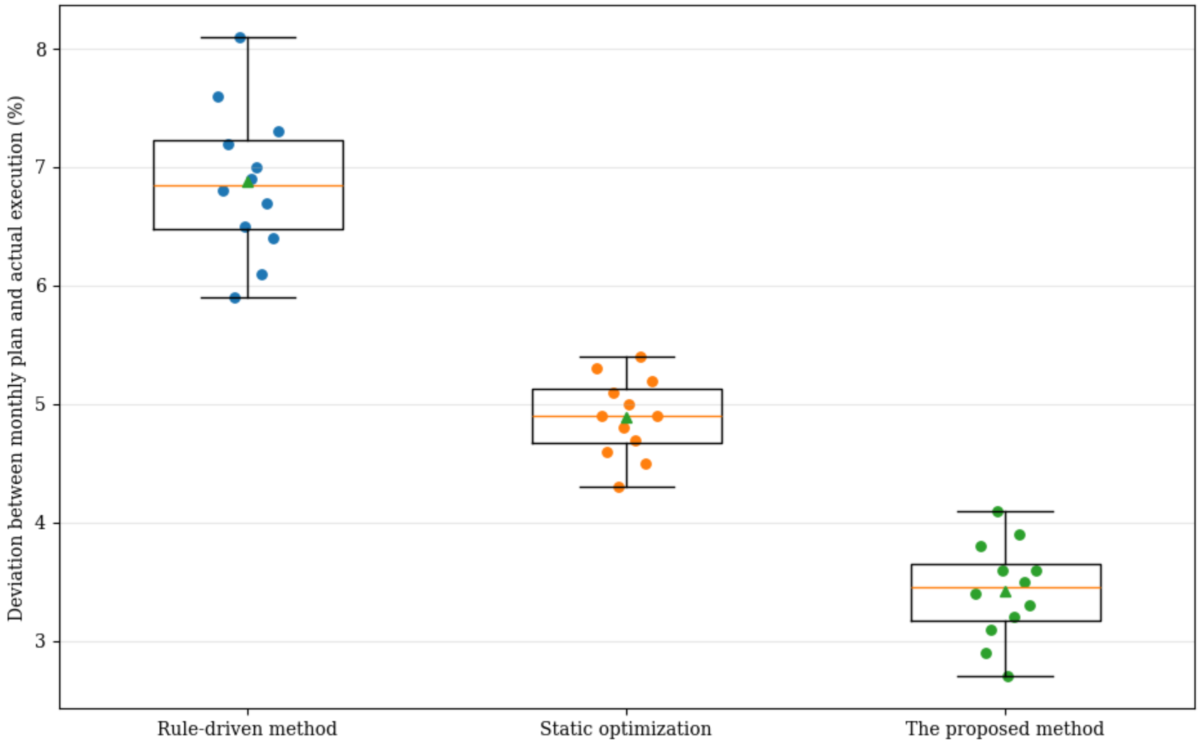


*Figure 6: Monthly planning output versus actual execution deviation*

In addition to hydrological and planning factors, unit operating conditions also have a direct impact on the scheduling results. In the document, detailed rules are defined for the grid-connected state, the load increasing process after grid-connected, the stable operation state and the load reducing process. It is pointed out that the identification results of the working conditions can provide support for operation optimization, fault warning and equipment management. Based on this logic, Fig. 7 compares the variation of the load tracking deviation before and after the condition correction. Without the introduction of working condition correction, the average deviation is 8.3 MW in the load increase stage and 7.1 MW in the load reduction stage after grid connection. After introducing the condition correction, the two decreased to 4.7MW and 3.9MW, respectively. The fluctuation band of the abnormal phase was narrowed from ± 6.2MW to ± 3.5MW, and the dispatch response delay was compressed from 2.6s to 1.7s. This result shows that condition identification can directly improve online execution stability after entering the scheduling loop.

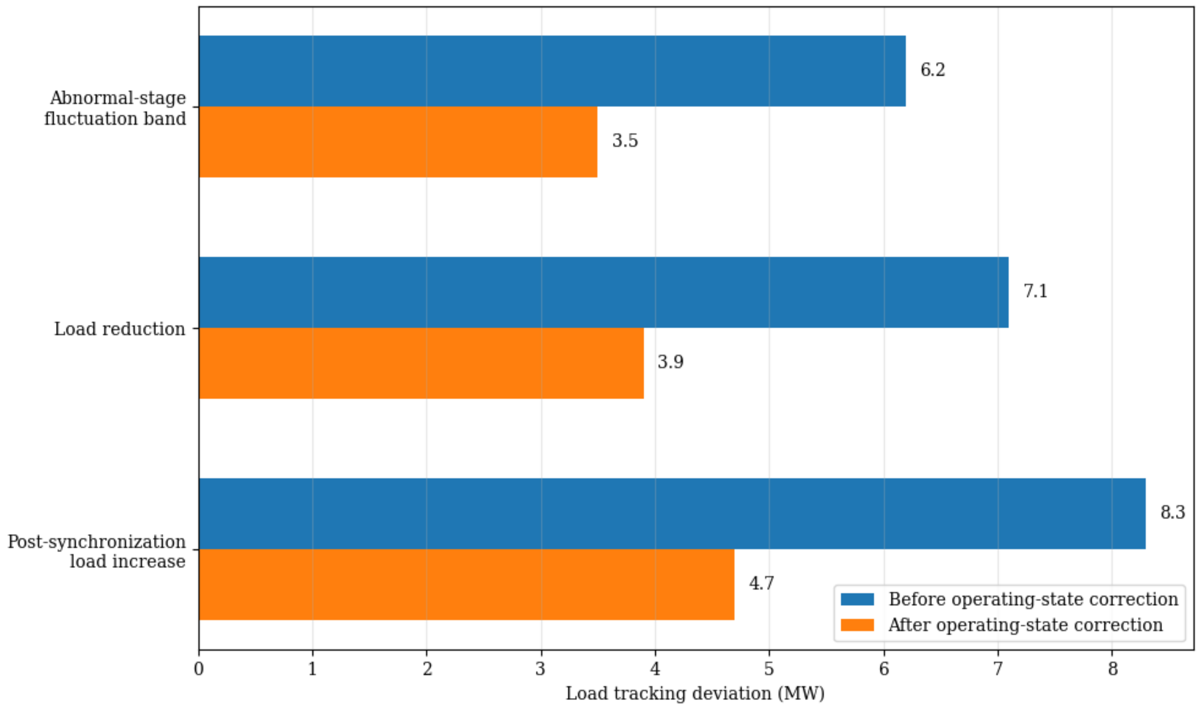


*Figure 7: Variation of load tracking deviation before and after condition correction*

Synthesizing the above results, the advantages of the proposed method are mainly reflected in the continuity of the resulting generation link and the stability of the execution link. The average flow prediction results of ten days can directly enter the medium and long term optimization scheduling process, the monthly plan and the weekly plan maintain a good decomposition consistency, and the working condition recognition results can also act on the output boundary and action correction process of the unit synchronously. Therefore, the economic dispatch of regional centralized power generation is no longer presented as separate prediction, planning and execution steps, but a continuous calculation process under a unified data input and rolling correction mechanism. For the task of this paper, this shows that only when the neural network optimization algorithm is embedded into the planning, rule response and state writeback links of the regional centralized control system, can it be stably transformed into executable scheduling results and continue to support subsequent operation corrections.

## 4.2 Implementation verification of regional centralized power generation economic dispatch system

After the analysis of the regional centralized power generation economic dispatch results, this paper further verifies the system implementation process. The focus of this section is no longer a single forecast value or a single scheduling result, but the execution stability of the regional centralized control platform in the continuous links such as data access, scheduling solution, plan preparation, plan reporting, working condition warning and feedback writeback. At the same time, the system receives hydrological monitoring data, ten-day average flow prediction results, annual monthly weekly planning parameters, unit maintenance information, working condition identification tags and historical account records, and integrates scheduling results, planning reports, approval documents, early warning events and writeback logs into the same service link. The purpose of this setting is to test whether the neural network optimization algorithm can continue to output stable results in the real scheduling process after entering the business platform, rather than staying in the independent solution stage.

As shown in Table 4, the performance of the system on the five types of core services is more balanced. The call success rate of data access service is 99.2%, the consensus rate of standardized results is 98.7%, and the average response delay is controlled at 1.2 s. The task completion rate of the scheduling solution service is 97.6%, the result agreement rate is 96.8%, and the average response delay is 1.8 s. The correct rate of the planning service is 96.4% under the linkage condition of annual, monthly and weekly planning. The completion rate of the file generation and submission process of the reporting service reached 99.1%. The trigger consistency rate and writeback integrity rate of the early warning analysis service reach 94.1% and 95.3%, respectively. This shows that the system does not rely on a single module to maintain operation, but maintains good link continuity in the case of multiple services online at the same time.

*Table 4: Verification results of core services of regional centralized power generation economic dispatch system*

| Functional Module | Invocation Success Rate / % | Result Consistency Rate / % | Write-Back Completeness Rate / % | Average Response Delay / s |
|---|---|---|---|---|
| Data Access Service | 99.2 | 98.7 | 98.9 | 1.2 |
| Dispatch Solving Service | 97.6 | 96.8 | 97.1 | 1.8 |
| Plan Preparation Service | 98.1 | 96.4 | 97.5 | 1.9 |
| Plan Submission Service | 99.1 | 98.6 | 99.0 | 1.4 |
| Warning Analysis Service | 95.0 | 94.1 | 95.3 | 1.7 |

Fig. 8 illustrates the first-layer analysis results of the system after the warning event is triggered. The interface takes an average of 1.7 seconds to complete information aggregation after a single event is triggered, and can synchronously display seven types of content, such as basic warning information, snapshot value, real-time value, monitoring view, correlation measurement point analysis, similar equipment comparison and event correlation. After 30 consecutive groups of early warning events were counted, the consistency rate between event recognition results and interface display results reached 94.1%, the average number of loading items of associated measurement points was 12, and the completion rate of key indicators reached 95.6%. From the perspective of the implementation effect, the system has been able to gather the information that was previously scattered in the monitoring of the point, the warning rules and the event record in the same interface, which makes the dispatcher not have to switch between different pages repeatedly when checking the exception, so as to improve the efficiency of the warning processing and the timeliness of the subsequent scheduling correction.

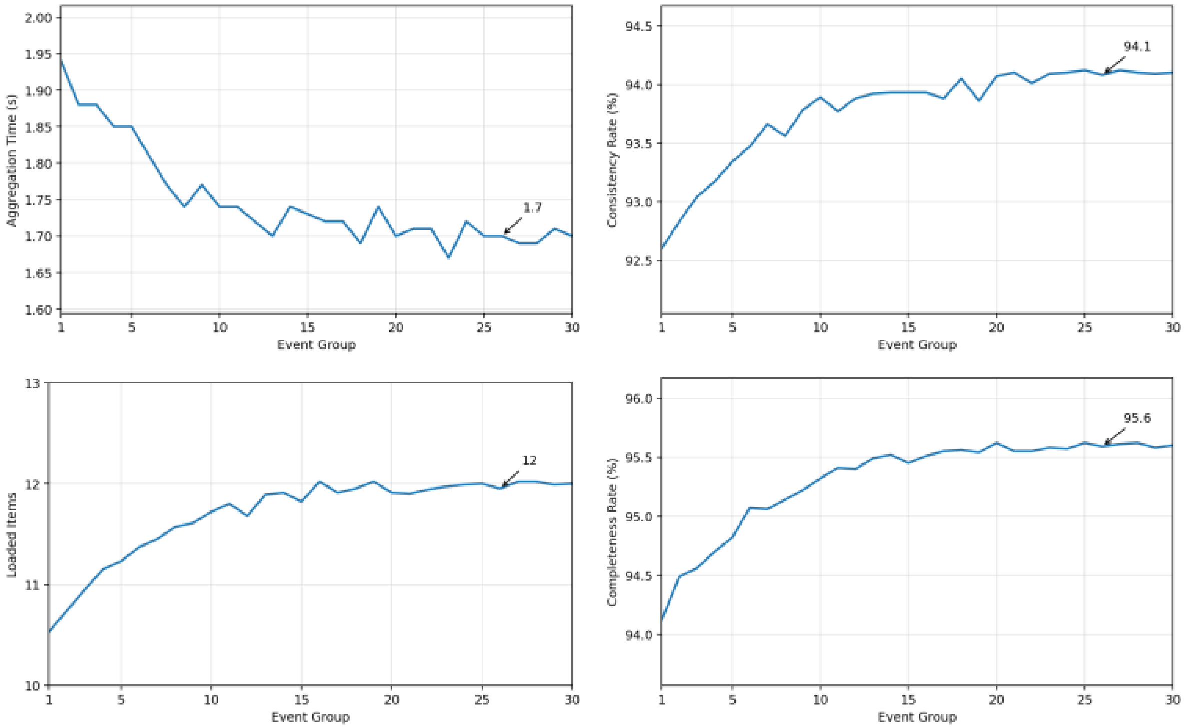


*Figure 8: Display of the analysis of the condition warning event*

In order to further identify the contribution of each module to the overall effect, an ablation experiment is designed. The whole system includes feature governance module, neural network scheduling engine, planning service and feedback governance service. The ablation experiment removes the feature governance module, planning service and feedback governance service in turn, and compares the accuracy of plan generation, the consistency rate of scheduling execution, the completion rate of early warning closed-loop and the average response delay. The results are shown in Table 5. The complete system achieves the best results on the four indicators, in which the accuracy rate of plan generation is 96.8%, the consistency rate of schedule execution is 95.4%, the completion rate of early warning closed-loop is 93.6%, and the average response delay is 1.8 s. After removing the feature governance module, the accuracy of plan generation dropped to 92.1%, indicating that the unified coding of multi-source data had a direct impact on scheduling calculation. After removing the planning service, the execution consistency rate dropped to 89.7%, indicating that if the algorithm output could not stably enter the planning layer, the overall effect of the system would be weakened. After removing the feedback governance service, the completion rate of the early warning closed loop decreases to 85.4%, and the response delay expands to 2.4 s, which indicates that the exception writeback and rule governance have an obvious supporting role in the regional centralized control scenario.

*Table 5: Ablation experimental results of regional centralized power generation economic dispatch system*

| System Configuration | Plan Generation Accuracy / % | Dispatch Execution Consistency Rate / % | Warning Closed-Loop Completion Rate / % | Average Response Delay / s |
|---|---|---|---|---|
| Complete System | 96.8 | 95.4 | 93.6 | 1.8 |
| Without Feature Governance Module | 92.1 | 91.8 | 90.2 | 2.0 |
| Without Plan Preparation Service | 90.4 | 89.7 | 91.1 | 2.1 |
| Without Feedback Governance Service | 94.2 | 92.6 | 85.4 | 2.4 |

Fig. 9 reflects the linkage results after the early warning events enter the deep analysis. In addition to the first event aggregation, the system will continue to perform similar equipment comparison, index feature analysis, measurement point analysis under the same working condition and historical event correlation after the abnormal trigger. The statistical results show that the average return time of the deep analysis stage is 1.9 s, the recall rate of similar historical events reaches 92.8%, the stability rate of the comparison results of the same working condition measurement points is 93.4%, and the support rate of the event interpretation results to the subsequent scheduling correction suggestions reaches 91.6%. This result shows that the system does not stop at a single alarm level, but can connect the current abnormal point, adjacent measurement points, samples of the same working condition and historical events into a complete event chain. For the economic dispatch of regional centralized power generation, this ability can make the abnormal fluctuations in the load increase process, stable operation state and load reduction process after grid connection enter the dispatch correction link faster, and reduce the impact of single point abnormal on the overall plan execution.

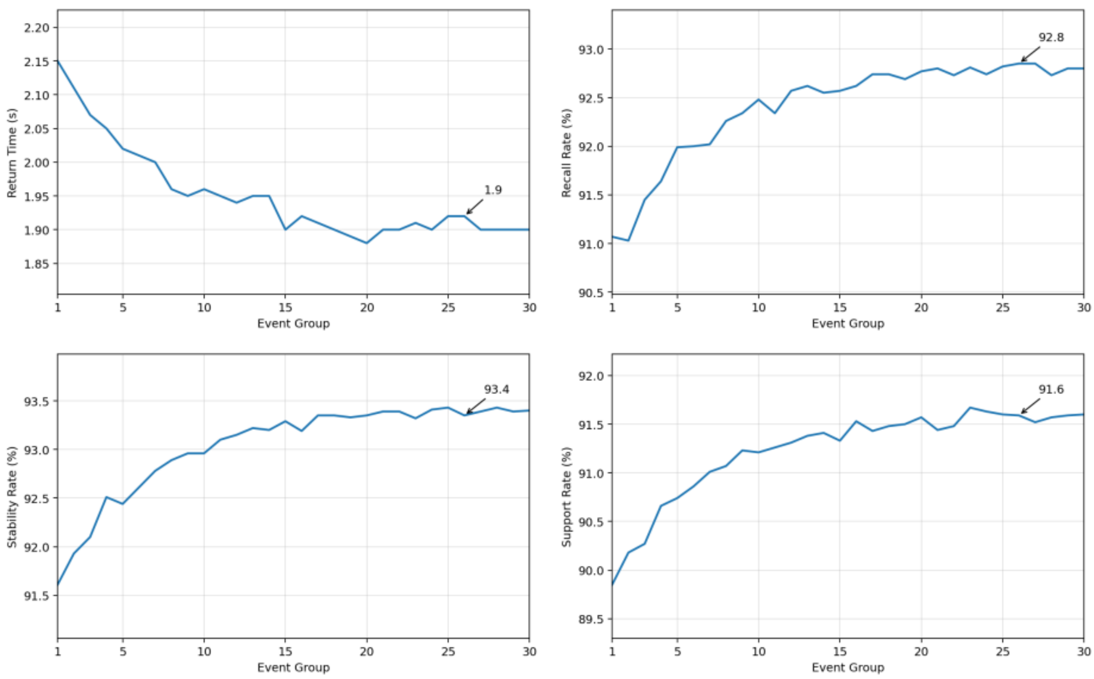


*Figure 9: Display of the condition warning event analysis*

Comprehensive Table 4, Table 5 and Fig. 8, Fig. 9, it can be seen that the realization effect of the regional centralized power generation economic dispatch system is mainly reflected in two links. One is the business execution chain based on data access, scheduling solution, plan generation and plan report, and the other is the feedback governance chain based on condition recognition, early warning trigger, event analysis and state writeback. The former ensures that the scheduling results can be stably generated and entered into the production plan, and the latter ensures that the abnormal state can be transmitted back in time for subsequent correction. The two links maintain continuous operation in the same system, which indicates that the regional centralized power generation economic dispatch system proposed in this paper not only has good algorithm carrying capacity, but also has good engineering adaptability and operation stability.

# 5 Discussion and Conclusion

Aiming at the operation characteristics of hydrologic, load, operating conditions and planning information changing in parallel in the regional centralized power generation scenario, this paper constructs an economic dispatch method for the joint operation of cascade power stations, and completes the collaborative design of neural network optimization algorithm and regional centralized control dispatch system. The results show that the proposed method can incorporate ten-day average traffic prediction, medium and long-term optimal scheduling, monthly and weekly planning, working condition identification and early warning writeback into the unified computing link, and achieve good comprehensive results in scheduling results, plan consistency and system execution stability. Compared with the rule-driven and static optimization methods, the proposed method performs better in the average flow prediction error of ten days, monthly planning deviation, water abandonment control and load tracking deviation, indicating that the neural network optimization algorithm can continuously improve the operation quality of regional centralized power generation after entering the planning service and feedback governance link.

However, the current method is still based on the existing station group structure, the existing measurement point system and the established planning rules. When the access range is further expanded, real-time data concurrency continues to improve, and temporary scheduling instructions become more frequent, the computational load, interface throughput capacity and rule coordination efficiency still need to be improved. Although the condition identification and scheduling correction have formed a closed loop, the adaptive ability of the system still needs to be further verified under the conditions of long-period disturbance, extreme incoming water fluctuation and cross-regional load linkage. Future research can focus on lightweight deployment, cross-regional collaborative scheduling, long-term robust learning, and planned writeback audit mechanism. Multi-station group transfer learning and edge-side online update mechanism are introduced to shorten the adaptation period of the model in new scenarios and enhance the continuous operation ability of the system under multi-module collaboration conditions.

# Funding

Science and Technology project of Hubei Energy Group Lou Shui Hydropower Co., LTD., project name "Research and Application of Key Technologies for Regional Hydropower Intelligent Remote Centralized Control", project number: KJCX202500274

# References

[1] Guo C, Wang X, Zheng Y, et al. Real-time optimal energy management of microgrid with uncertainties based on deep reinforcement learning[J]. Energy, 2022, 238: 121873.

[2] Hu C, Cai Z, Zhang Y, et al. A soft actor-critic deep reinforcement learning method for multi-timescale coordinated operation of microgrids[J]. Protection and Control of Modern Power Systems, 2022, 7(1): 29.

[3] Goh H H, Huang Y, Lim C S, et al. An assessment of multistage reward function design for deep reinforcement learning-based microgrid energy management[J]. IEEE transactions on smart grid, 2022, 13(6): 4300-4311.

[4] Alabdullah M H, Abido M A. Microgrid energy management using deep Q-network reinforcement learning[J]. Alexandria Engineering Journal, 2022, 61(11): 9069-9078.

[5] Muriithi G, Chowdhury S. Deep Q-network application for optimal energy management in a grid-tied solar PV-Battery microgrid[J]. The Journal of Engineering, 2022, 2022(4): 422-441.

[6] Phan B C, Lee M T, Lai Y C. Intelligent deep-Q-network-based energy management for an isolated microgrid[J]. Applied Sciences, 2022, 12(17): 8721.

[7] Ding L, Lin Z, Shi X, et al. Target-value-competition-based multi-agent deep reinforcement learning algorithm for distributed nonconvex economic dispatch[J]. IEEE Transactions on power systems, 2022, 38(1): 204-217.

[8] Han X, Mu C, Yan J, et al. An autonomous control technology based on deep reinforcement learning for optimal active power dispatch[J]. International Journal of Electrical Power & Energy Systems, 2023, 145: 108686.

[9] Lin F J, Chang C F, Huang Y C, et al. A deep reinforcement learning method for economic power dispatch of microgrid in OPAL-RT environment[J]. Technologies, 2023, 11(4): 96.

[10] Liu D, Zang C, Zeng P, et al. Deep reinforcement learning for real-time economic energy management of microgrid system considering uncertainties[J]. Frontiers in Energy Research, 2023, 11: 1163053.

[11] Feng B, Liu Z, Huang G, et al. Robust federated deep reinforcement learning for optimal control in multiple virtual power plants with electric vehicles[J]. Applied Energy, 2023, 349: 121615.

[12] Xiao H, Pu X, Pei W, et al. A novel energy management method for networked multi-energy microgrids based on improved DQN[J]. IEEE Transactions on Smart Grid, 2023, 14(6): 4912-4926.

[13] Zhang X, Wang Q, Yu J, et al. A multi-agent deep-reinforcement-learning-based strategy for safe distributed energy resource scheduling in energy hubs[J]. Electronics, 2023, 12(23): 4763.

[14] Abid M S, Apon H J, Hossain S, et al. A novel multi-objective optimization based multi-agent deep reinforcement learning approach for microgrid resources planning[J]. Applied Energy, 2024, 353: 122029.

[15] Gao Z, Kang W, Chen X, et al. Optimal economic dispatch of a virtual power plant based on gated recurrent unit proximal policy optimization[J]. Frontiers in Energy Research, 2024, 12: 1357406.

[16] Wang X, Zhong H, Zhang G, et al. Adaptive look-ahead economic dispatch based on deep reinforcement learning[J]. Applied Energy, 2024, 353: 122121.

[17] Yu Z, Zheng W, Zeng K, et al. Energy optimization management of microgrid using improved soft actor-critic algorithm[J]. International Journal of Renewable Energy Development, 2024, 13(2): 329-339.

[18] Ding L, Cui Y, Yan G, et al. Distributed energy management of multi-area integrated energy system based on multi-agent deep reinforcement learning[J]. International Journal of Electrical Power & Energy Systems, 2024, 157: 109867.

[19] Durán F, Pavón W, Minchala L I. Forecast-based energy management for optimal energy dispatch in a microgrid[J]. Energies, 2024, 17(2): 486.

[20] Hu C, Li D, Zhao W, et al. Deep reinforcement learning-based scheduling for integrated energy system utilizing retired electric vehicle battery energy storage[J]. Journal of Energy Storage, 2024, 97: 112774.