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A Data-Driven Multi-Scale Source–Grid–Load–Storage Collaborative Dispatching Method for Distribution Systems

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Abstract

Currently, distribution system scheduling faces significant uncertainty and dynamic complexity due to the large-scale integration of diverse heterogeneous entities, while conventional approaches suffer from limited capability in modeling user behavior responses and ensuring dispatch accuracy, making them inadequate for source–grid–load–storage collaborative optimization. To address this, this paper proposes a data-driven multi-scale coordinated scheduling method for distribution systems, in which distributed generation outputs, load responses, and energy storage states are extracted and modeled using an improved exponential smoothing technique; a hierarchical and time-divided optimization framework is then developed by combining machine learning and probabilistic modeling with spatial correlation analysis to enhance renewable generation and load forecasting accuracy; and finally, a two-stage robust optimization model considering scenario uncertainties is established through typical scenario generation and uncertainty set constraints to achieve dispatch strategies that balance economic efficiency and low-carbon objectives and supply reliability under fluctuating renewable outputs and dynamic load variations. Simulation results demonstrate that the proposed method reduces total operating cost by 16.4%, decreases carbon emissions by 10.7%, and lowers electricity purchase fluctuation by 8.75%, thereby significantly enhancing system flexibility and adaptability to renewable energy uncertainties and providing a novel pathway for the development of active and intelligent distribution systems.

Keywords: source–network–load–storage coordination; data-driven; robust optimization; low-carbon economy



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1. Introduction

With the large-scale grid connection of multiple heterogeneous entities such as distributed energy and energy storage systems, the operation of distribution systems shows significant randomness and uncertainty. Traditional dispatching methods rely on empirical assumptions or single-time-scale models, making it difficult to accurately capture these dynamic characteristics [1,2]. The data-driven distribution network dispatching method can support the refined modeling and prediction of the spatio-temporal correlation between sources, grids, loads, and storage and meet the dispatching requirements of multi-objective optimization. Therefore, the data-driven distribution network dispatching method can better adapt to the development trends of energy transformation and power system upgrading.

At present, the dispatching of distribution networks mainly focuses on the challenges brought by the access of multiple heterogeneous entities and the coordination of various flexible regulation resources. The capacity boundary and voltage boundary models of distribution networks were established, and a general simplification and acceleration method for distribution network optimization problems was proposed [3]. Ref. [4] addressed the significant differences among various energy storage types and the associated coordination difficulty and proposes a joint day-ahead and intraday dispatching framework. Ref. [5] proposed a day-ahead optimal dispatch strategy for active distribution networks based on improved deep reinforcement learning. Another study proposed a two-stage optimal scheduling method considering different control time scales to maximize renewable energy utilization (or penetration) in active distribution networks in active distribution networks [6]. Ref. [7] aimed to address the issues of strong uncertainty and heavy computational burden brought about by the integration of large-scale distributed power sources into the distribution network at the economic dispatching level; a distributed collaborative optimization model based on a data-driven security domain was established in a multi-period schedulable domain. Ref. [8] established a coordinated and optimized dispatching method for distribution networks and photovoltaic storage charging stations considering the coupling of electrical energy and reserve. This method not only alleviates the regulatory pressure brought to the distribution network by the large-scale access of photovoltaic storage charging stations but also achieves a balance between the economic and reliable dispatching of the distribution network [8]. Ref. [9] proposed an active distribution network optimization control strategy based on multi-objective optimization, which reduced the dispatching cost of the distribution network and improved the utilization rate of clean energy without lowering user satisfaction. However, the above-mentioned research only considered the multi-time scale distribution network optimization dispatching methods and failed to conduct hierarchical modeling of the source–grid–load–storage architecture of the distribution network [9].

At present, most distribution network optimizations aim at the safe and economic operation of distribution networks, and robust optimization methods are often adopted to cope with the changes brought about by uncertainties. Aiming at the uncertainty problem of various controllable resources brought to the AC/DC hybrid distribution network by the high proportion of renewable energy access, a multi-objective robust optimization model considering the uncertainties of power generation and load of the distribution network was established [10]; Ref. [11] analyzed the historical data of wind and solar output by using the probability density function and established a robust optimization operation model for active distribution networks based on the minimum confidence interval of the beta distribution of distributed energy [11]. Ref. [12] established a distributed robust optimization day-ahead scheduling model for the collaboration of distribution networks and multiple micronetworks to address the issues of data privacy and uncertainty in new energy output among various micronetworks [12]. Ref. [13] established a division model for distributed power source clusters in distribution networks by combining the modularity index and proposed a robust balance index for the flexible supply and demand of distributed power source clusters [13]. Ref. [14] characterized the features of wind and solar power stations and fast charging stations by using polyhedral uncertain sets, and it constructed a two-stage robust scheduling of day–day and intraday for an active distribution network based on the power demand of integrated stations to optimize power flow and reduce network losses and operating costs [14]. Ref. [15] improved the power flow optimization and node voltage deviation of active distribution networks by quantifying risk preferences and constructing an improved two-stage robust economic dispatch [15]. However, most of the above-mentioned studies describe uncertainty by using probability

distribution, interval constraints, or fuzzy sets, all of which rely on static uncertainty sets and fail to deeply integrate the characteristics of data-driven dynamic modeling. In contrast, the data-driven method does not rely on the preset distribution or fixed interval to describe the uncertainty. Instead, it learns the time-varying statistical characteristics and related structures of source–load disturbances from historical and online operation data and constructs a scrollable and updated uncertainty set accordingly, thereby reducing model mismatch and improving scheduling feasibility and economy.

Therefore, in view of the above-mentioned problems of failing to stratify the source–grid–load–storage architecture of the distribution network and failing to combine the data-driven dynamic modeling characteristics, this paper proposes a data-driven multi-scale source–grid–load–storage collaborative dispatching method for distribution systems. Based on the existing data on distributed energy output, load, and energy storage status, a data prediction model is constructed through machine learning and probabilistic modeling methods, and a multi-time-scale and multi-level optimization scheduling framework is built. A multi-objective function optimization scheduling model with the lowest system operation cost, the highest renewable energy consumption rate, and the lowest load loss rate is established. Based on historical data, a typical scene operation library is established. Uncertainty is characterized by the scene generation method. Based on this, a day-real-time two-stage robust optimization model is established to propose a robust scheduling method adapted to source–load uncertainty. Simulation analysis is conducted to verify the effectiveness of the proposed method.

2. Modeling of Dynamic Characteristics of Source–Grid–Load–Storage Based on Data-Driven Coupling Architecture

The data-driven source–grid–load–storage coupling architecture of the distribution network, by leveraging advanced data acquisition, processing, and analysis technologies, enables efficient and coordinated operation of distributed power sources and loads [16]. Its core objective is to enhance the flexibility, reliability, and economy of the distribution network through data empowerment in order to adapt to the high proportion of renewable energy access and diverse load demands. The specific structure is shown in Figure 1.

The equation of the energy flow balance relationship among electricity, heat, and hydrogen is shown in Equation (1):

$$\begin{bmatrix} P_t^E \\ P_t^H \\ P_t^R \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 1 & 0 & 0 \\ -1 & \zeta_{eth} & 0 \\ 0 & -1 & \zeta_{hte} \\ -1 & 0 & \zeta_{htr} \\ \zeta_{hte} & -1 & 0 \end{bmatrix}^T \begin{bmatrix} P_t^{PG} \\ P_t^{WD} \\ P_{EL,t} \\ P_{HB,t} \\ P_{EB,t} \\ P_{HFC,t} \end{bmatrix} \quad (1)$$

$$\begin{bmatrix} P_{E,t}^L \\ P_{H,t}^L \\ P_{R,t}^L \end{bmatrix} = \begin{bmatrix} P_t^E \\ P_t^H \\ P_t^R \end{bmatrix} + \begin{bmatrix} P_{E,t}^{pur} \\ P_{H,t}^{pur} \\ P_{R,t}^{pur} \end{bmatrix} + \begin{bmatrix} P_{dc,t}^{BES} \\ P_{dc,t}^{HST} \\ P_{dc,t}^{HSD} \end{bmatrix} - \begin{bmatrix} P_{cr,t}^{BES} \\ P_{cr,t}^{HST} \\ P_{cr,t}^{HSD} \end{bmatrix} \quad (2)$$

where, P_t^E , P_t^H , P_t^R generate electrical, hydrogen, and thermal power for the equipment; P_t^{WD} represents the wind power output at time t ; P_t^{PG} represents the output power of photovoltaic power generation at time t ; $P_{E,t}^{pur}$, $P_{H,t}^{pur}$, $P_{R,t}^{pur}$ represent the power purchased by the power grid at time t ; $P_{E,t}^L$, $P_{H,t}^L$, $P_{R,t}^L$ represent the power consumption of the electrical load, hydrogen load, and heat load at time t , respectively; $P_{dc,t}^{BES}$, $P_{cr,t}^{BES}$ are, respectively, the charging and discharging powers of battery energy storage (BES); $P_{dc,t}^{HST}$, $P_{cr,t}^{HST}$ are, respectively, the charging and discharging powers of the hydrogen storage tank (HST);

$p_{cr,t}^{HSD}$, $p_{dc,t}^{HSD}$ respectively represent the charging and discharging power of the heat storage device; $P_{EL,t}$, $P_{EB,t}$, $P_{HB,t}$, $P_{HFC,t}$ are electrolytic cells, electric boilers, hydrogen boilers, and hydrogen–oxygen fuel cells; ζ_{eth} represents the hydrogen production efficiency; ζ_{etr} represents the heat generation efficiency; ζ_{htr} represents the hydrogen production efficiency; and ζ_{hte} represents the power generation efficiency.

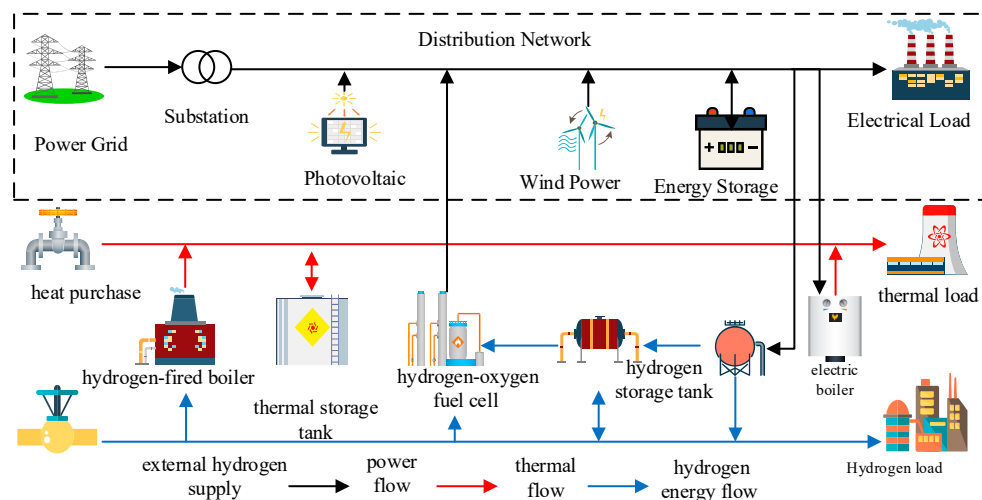


Figure 1. Data-driven coupling architecture of source–grid–load–storage in distribution networks.

2.1. Modeling of Output Characteristics of Energy Supply Side

In a multi-energy collaborative distribution system, the energy supply side includes not only local distributed energy sources such as wind power and photovoltaic power, but also centralized energy supply from the power grid, heating network, and external hydrogen sources [17]. In this paper, the improved cubic exponential smoothing method is adopted to model its output time series and construct a data-driven output characteristic model of distributed power sources.

In the improved cubic exponential smoothing method, the dynamic smoothing coefficient $\Psi_{k,t}$ is a function of t , which changes with the change in prediction number k and time t , and can adapt well to the change trend of time series data with time fluctuation. In order to judge whether the smoothing coefficient $\Psi_{k,t}$ is accurate, this study introduces two evaluation parameters: mean square error and relative error. The mean square error formula is shown in Formula (3), and the relative error formula is shown in Formula (4):

$$\sigma_{jfc} = \sqrt{\frac{(P_1^b - N_1^b)^2 + (P_2^b - N_2^b)^2 + \dots + (P_t^b - N_t^b)^2}{t}} \quad (3)$$

Among them, P_t^b is the predicted value of b parameter, N_t^b is the actual value, and σ_{jfc} is the mean square error. The smaller the mean square error, the higher the data prediction accuracy and the more reliable the data.

$$\begin{cases} \delta_{xd} = \Delta_t^b / N_t^b \times 100\% \\ \Delta_t^b = P_t^b - N_t^b \end{cases} \quad (4)$$

where δ_{xd} is the relative error and Δ_t^b is the absolute error.

By performing smoothing operations on historical data of wind power, photovoltaic power, thermal power, electricity, and hydrogen loads, the prediction results of wind power, photovoltaic power, electricity, thermal power, and hydrogen load data can be expressed as:

$$\begin{cases} \phi_{k,t} = \frac{\delta_k}{1-(1-\delta_k)^t} \\ P_{k,t+T}^b = h_{k,t} + j_{k,t}T + c_{k,t}T^2 \\ h_{k,t} = 3V_{k,t}^{(1)} - 3V_{k,t}^{(2)} + V_{k,t}^{(3)} \\ j_{k,t} = \frac{\phi_{k,t}}{2(1-\phi_{k,t})^2} [(6-5\phi_{k,t})V_{k,t}^{(1)} \\ -(10-8\phi_{k,t})V_{k,t}^{(2)} + (4-3\phi_{k,t})V_{k,t}^{(3)}] \\ g_{k,t} = \frac{\phi_{k,t}^2}{2(1-\phi_{k,t})^2} (V_{k,t}^{(1)} - 2V_{k,t}^{(2)} + V_{k,t}^{(3)}) \end{cases} \quad (5)$$

where $\phi_{k,t}$ is the adaptive dynamic smoothing coefficient, k is the number of predictions, δ_k is the adaptive smoothing factor, $P_{k,t+T}^b$ is the data prediction result, $h_{k,t}$, $j_{k,t}$, and $g_{k,t}$ are all prediction coefficients, and $V_t^{(1)}$, $V_t^{(2)}$ and $V_t^{(3)}$ are the first-order, second-order, and third-order exponential smoothing values, respectively.

Compared with the traditional three exponential smoothing method, based on the historical data of wind power in March in a certain place, two of the prediction results are selected and displayed as shown in Figure 2.

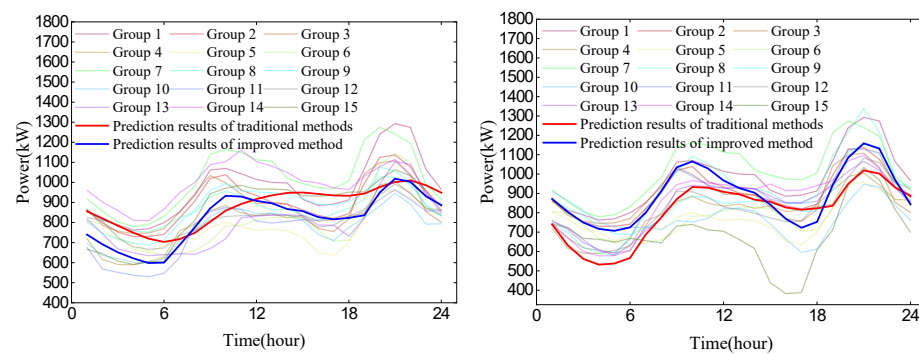


Figure 2. Comparison diagram of prediction results.

2.2. Modeling of State Characteristics of Energy Storage System

The flexible charging and discharging characteristics of the energy storage system (BESS) undertake the key functions of peak shaving and valley filling as well as power balance in multi-party collaborative dispatching. The state characteristics of the energy storage system are modeled, mainly focusing on the evolution of its energy storage state (state of charge, SOC) and the constraints of charging and discharging power to enable it to exert quantifiable value in multi-energy coordination and multi-temporal and spatial scheduling. Various energy storage models are shown as follows:

2.2.1. BES Model

$$E_t^{\text{BES}} = E_{t-1}^{\text{BES}} + (P_{\text{cr},t}^{\text{BES}} \cdot \zeta_{\text{cr}}^{\text{BES}} + P_{\text{dc},t}^{\text{BES}} / \zeta_{\text{dc}}^{\text{BES}}) \quad (6)$$

where E_t^{BES} is the electrical energy stored in the energy storage battery at time t , $\zeta_{\text{cr}}^{\text{BES}}$ is the charging efficiency of the energy storage battery, and $\zeta_{\text{dc}}^{\text{BES}}$ is the discharging efficiency of the energy storage battery.

2.2.2. HST Model

$$H_t^{\text{HST}} = H_{t-1}^{\text{HST}} + (P_{\text{cr},t}^{\text{HST}} \cdot \zeta_{\text{cr}}^{\text{HST}} + P_{\text{dc},t}^{\text{HST}} / \zeta_{\text{dc}}^{\text{HST}}) \quad (7)$$

where H_t^{HST} is the hydrogen stored in the hydrogen storage tank (HST) at time t , $\zeta_{\text{cr}}^{\text{HST}}$ is the hydrogen storage efficiency of the hydrogen storage tank, and $\zeta_{\text{dc}}^{\text{HST}}$ is the hydrogen release efficiency of the hydrogen storage tank.

2.2.3. HSD Model

$$R_t^{\text{HSD}} = R_{t-1}^{\text{HSD}} + \left(P_{\text{cr},t}^{\text{HSD}} \cdot \zeta_{\text{cr}}^{\text{HSD}} + P_{\text{dc},t}^{\text{HSD}} / \zeta_{\text{dc}}^{\text{HSD}} \right) \quad (8)$$

where R_t^{HSD} is the heat stored in the heat storage tank at time t , $\zeta_{\text{cr}}^{\text{HSD}}$ is the heat storage efficiency of the heat storage tank, and $\zeta_{\text{dc}}^{\text{HSD}}$ is the heat release efficiency of the heat storage tank.

The output power of the power grid, heating network, and external hydrogen purchase should satisfy the following constraint relations:

$$\begin{cases} 0 \leq P_{\text{E},t}^{\text{pur}} \leq P_{\text{E},t}^{\text{pur,max}} \\ 0 \leq P_{\text{R},t}^{\text{pur}} \leq P_{\text{R},t}^{\text{pur,max}} \\ 0 \leq P_{\text{H},t}^{\text{pur}} \leq P_{\text{H},t}^{\text{pur,max}} \end{cases} \quad (9)$$

where, $P_{\text{E},t}^{\text{pur,max}}$, $P_{\text{R},t}^{\text{pur,max}}$, $P_{\text{H},t}^{\text{pur,max}}$ represent the maximum power of electricity purchased from the power grid, heat purchased from the heat network, and external hydrogen purchased at time t , respectively.

In the process of low-carbon economic dispatching, it is necessary to conduct data prediction on the output power of wind power and photovoltaic power on typical days. The output power of wind power and photovoltaic power must first meet the following constraints:

$$\begin{cases} 0 \leq P_{\text{WD},t} \leq P_{\text{WD},t}^{\text{max}} \\ 0 \leq P_{\text{PG},t} \leq P_{\text{PG},t}^{\text{max}} \end{cases} \quad (10)$$

where $P_{\text{WD},t}^{\text{max}}$ and $P_{\text{PG},t}^{\text{max}}$ are the maximum power generation power of wind power and photovoltaic at time t , respectively.

3. Spatio-Temporal Information Integrated Prediction Method for Distribution Network Based on Data-Driven Method

To cope with the large-scale access and uncertain disturbances of multiple elements such as source–grid–load–storage in the distribution system, it is necessary to construct a hierarchical and time-sharing collaborative dispatching architecture [18]. Layering corresponds to the division of spatial or control levels, and time-sharing corresponds to decisions of different time scales. The combination of the two can reduce the complexity of the problem and improve real-time performance and reliability. Regional integrated energy systems exhibit significant temporal characteristics on time scales such as day-ahead and intraday, and city-level systems across regions also show typical seasonal differences.

3.1. Construction of Source–Load Power Prediction Model Considering Spatio-Temporal Correlation

In the power distribution system, based on the spatio-temporal characteristics of the energy production and consumption ends in multiple regions and considering dynamic interactions, a wind–solar–load power prediction model based on the spatial correlation of multiple regions is established to provide more accurate and efficient support for energy management. It mainly includes the spatio-temporal distribution characteristic models of wind power, photovoltaic power, and different load demands.

Considering that wind power, photovoltaic power, and load have significant spatial correlation between different regions, single-node time series prediction is difficult to reflect cross-regional synchronous fluctuations and propagation effects. This paper describes the relationship between related regions through space. The Spearman rank correlation coefficient is used to analyze the nonlinear relationship between variables and quantify the degree of interaction between each parameter. It does not depend on the specific

distribution assumption of the data. Based on the Spearman rank correlation coefficient and the spatial position coordinates of IES in different regions, the spatial correlation coefficient of IES wind turbine in the i th region is established:

$$d_{n,i} = \left(1 - \frac{6 \sum_{j=1}^m z_j^2}{m(m^2 - 1)} \right) \cdot \frac{\sqrt{\sum_{r=1}^3 (l_{n,r} - l_{0,r})^2}}{l_{0,r}} \quad (11)$$

where $d_{i,n}$ is the spatial correlation coefficient of the x wind turbine in the IES of the i region, m is the sample size of the wind speed historical data, z_j^2 is the sum of the rank difference squares of the j th sample data, $l_{i,r}$ is the r -dimensional coordinate of the x wind turbine, and $l_{0,r}$ is the reference coordinate of the wind speed measured by the wind farm.

Similarly, based on the Spearman rank correlation coefficient, the spatial correlation coefficient of photovoltaic power generation in the i th region is established. The specific model is as follows:

$$d_{g,i} = \left(1 - \frac{6 \sum_{e=1}^w p_e^2}{\beta(\beta^2 - 1)} \right) \cdot \left(\frac{l_g - l_0}{l_0} \right) \quad (12)$$

where $d_{g,n}$ is the spatial correlation coefficient of the g th photovoltaic power generation plate in the IES of the i th region, β is the sample size of the historical data of the light intensity, p_e^2 is the sum of the rank difference squares of the sample data of the e th region, l_g is the spatial coordinate of the g th photovoltaic power generation plate, and l_0 is the reference coordinate of the light intensity measured by the photoelectric field.

The spatial and temporal distribution characteristics model of seasonal load can be expressed as:

$$P_s^{\text{Load,E}} = \frac{G \cdot \sum_{t=1}^T P_t^{\text{Load}}}{T} + \psi_d \cos\left(\frac{2\pi t}{T} + \theta_d\right) + \psi_s \cos\left(\frac{2\pi t}{T_s} + \theta_s\right) \quad (13)$$

where $P_s^{\text{Load,E}}$ is the load power in s season, P_t^{Load} is the load at time t , ψ_d is the daily load fluctuation amplitude, θ_d is the phase of the load peak, and T is the time period of one day. ψ_s is the amplitude of seasonal load fluctuation, θ_s is the phase of the season where the load peak is located, and T_s is the number of hours in the first quarter.

The weight benchmark of the spatial weight matrix $W = [w_{sj}]$ is obtained by summarizing the spatial correlation coefficients of wind power/photovoltaic power calculated by the Formula (12) in the regional layer, and then normalized by rows and $w_{ss} = 0$, so as to form a normalized spatial weight matrix satisfying $\sum_j w_{sj} = 1$, which is used for the spatial lag term in Formula (14).

$$\begin{cases} Y_k(s, t) = B_k(s, t) + \sum_{\tau=1}^p \Gamma_n Y_k(s, t - \tau) \\ + m \sum_{j=1}^N w_{sj} Y_k(j, t) \\ + \varepsilon_k(s, t) \\ B_{wt}(s, t) = f_{\text{aero}}(v(s, t)) \\ B_{pv}(s, t) = f_{pv}(G(s, t), T_m(s, t)) \\ B_\ell(s, t) = \gamma_0 + \gamma_1 T(s, t) + \gamma_2 D(t) \end{cases} \quad (14)$$

where $k \in wt, pv, \text{load}$. $Y_k(s,t)$ represents the corresponding power wind power P_{wt} , photovoltaic P_{pv} , and load P_{load} . $B_k(s,t)$ is the baseline function. Γ_n is the uniform time autoregressive coefficient. m is the spatial lag coefficient. w_{sj} is the normalized spatial weight. ε_k is the noise term. v, G, T_m , and T represent wind speed, irradiance, component temperature, and ambient temperature, respectively. $D(t)$ is the calendar dummy variable, and γ_0, γ_1 , and γ_2 are the load baseline regression coefficients.

3.2. Source–Load Probabilistic Collaborative Prediction Based on TCN

Facing the problem of increased uncertainty and spatio-temporal coupling caused by the coexistence of high-permeability renewable and flexible loads, this paper proposes a source–load probabilistic collaborative prediction method based on TCN. Based on retaining the existing load point prediction as a strong prior, consistency constraints are introduced to uniformly output multi-step confidence intervals for photovoltaic, wind power, load, and net load, enhancing the stability and engineering availability of the prediction and providing support for the coordinated optimization of the economy and safety of the distribution network.

Let the node/region $i \in N$, the time index $t \in T$, and the prediction step size set $H = \{1, \dots, H\}$. The variable type $v \in \{PV, WT, L\}$, respectively, represents photovoltaic, wind power and load. Given a multivariable historical and exogenous feature sequence with a window length of ω , the goal is to output a probability prediction for each (i, h, v) .

$$\begin{cases} Z_{i,t} = \text{TCN}_\theta(X_{i,t-\omega+1:t}) \\ \hat{y}_{i,t+1:t+H}^{(\tau),v} = f_v^{(\tau)}(Z_{i,t}) \end{cases} \quad (15)$$

where TCN_θ is a temporal convolutional network, i is a node, and $Z_{i,t}$ is the hidden representation vector of node i at time t .

Source–load cooperative consistency:

$$\begin{cases} \mathcal{L}_{\text{coh}} = \sum_{i,t,h} \sum_{\tau \in \mathcal{T}_q} \left(\hat{D}_{i,t+h}^{(\tau)} - \left(\hat{L}_{i,t+h}^{(\tau)} - \hat{R}_{i,t+h}^{(\tau)} \right) \right)^2 \\ \hat{R}^{(\tau)} = \hat{p}^{(\tau),PV} + \hat{p}^{(\tau),WT} \end{cases} \quad (16)$$

where h is the prediction step; $\mathcal{T}_q$ is the sample set; $\mathcal{L}_{\text{coh}}$ is the consistency loss; $\hat{D}_{i,t+h}^{(\tau)}$, $\hat{L}_{i,t+h}^{(\tau)}$, and $\hat{R}_{i,t+h}^{(\tau)}$ are the predicted values of net load, total load, and renewable power generation, respectively; and $\hat{p}^{(\tau),PV}$, $\hat{p}^{(\tau),WT}$ are the predicted output of wind power and photovoltaic power.

Smooth regular expression:

$$\begin{cases} \mathcal{L}_{\text{quant}} = \sum_{v,i,t,h} \sum_{\tau \in \mathcal{T}_q} \rho_\tau \left(y_{i,t+h}^v - \hat{y}_{i,t+h}^{(\tau),v} \right) \\ \min_{\theta} \mathcal{L} = \mathcal{L}_{\text{quant}} + \lambda_{\text{coh}} \mathcal{L}_{\text{coh}} + \lambda_{\text{sm}} \mathcal{L}_{\text{sm}} \end{cases} \quad (17)$$

$\mathcal{L}_{\text{quant}}$ is the quantile regression loss, $\mathcal{L}_{\text{sm}}$ is the smoothing loss, and λ_{sm} and λ_{coh} are hyperparameters.

Constraints and boundaries:

$$\begin{cases} \hat{p}_{i,t+h}^{(\tau),PV} \in [0, p_{i,t+h}^{\text{max},PV}] \\ \hat{p}_{i,t+h}^{(\tau),WT} \in [0, p_{i,t+h}^{\text{max},WT}] \\ \hat{L}_{i,t+h}^{(\tau)} \geq 0 \end{cases} \quad (18)$$

The TCN network architecture design in this paper is used to process sequence data. The input dimension is 24 dimensions, the hidden layer dimension is 64 dimensions, and the output dimension is also 24 dimensions. The network contains four residual blocks. Each residual block uses a one-dimensional convolution with a convolution kernel size of 3, uses an increasing expansion rate [1, 2, 4, 8] to gradually expand the receptive field, and finally reaches a 31-step receptive field, thereby effectively capturing long-distance time dependence. The activation function adopts ReLU combined with the WeightNorm regularization method to improve training stability and model performance. The dropout rate is 0.2, which is used to prevent overfitting; the optimizer uses the Adam algorithm to achieve efficient parameter updating.

4. Distribution Network Source–Load Coordinated Dispatching Considering Two-Stage Robust Optimization

With the deep penetration of distributed energy sources and flexible loads in the distribution network, the system operation presents high uncertainty and strong coupling.

Traditional deterministic dispatching models are difficult to effectively cope with multi-source disturbances such as wind and photovoltaic output fluctuations, user load responses, and energy storage state changes, resulting in difficulty in balancing economy and safety [19,20].

To this end, this section introduces a two-stage robust optimization framework: formulating power purchase, unit output, and energy storage plans in advance at the day-ahead level and making flexible corrections according to uncertain disturbances at the real-time level to achieve safe operation and economic optimization of source–load coordination.

4.1. Two-Stage Objective Function

Under the two-stage robust optimization framework, the dispatching objectives are divided into the first stage (day-ahead planning objective) and the second stage (intraday correction objective).

(1) First-stage objective: Economic planning

The first stage aims to minimize the operation cost, which mainly includes power purchase cost, distributed power source cost, and reserve cost.

$$f_1(x) = \sum_t \left[c_t^{\text{grid}} P_t^{\text{grid}} + \sum_i c_i^{\text{DG}} P_{i,t}^{\text{DG}} + \sum_i c_i^{\text{DR,cap}} z_{i,t}^{\text{DR}} + \omega_Y \sum_{t=1}^T \gamma_Y^t \left| \Delta Y_{\text{pc}}^t \right| \right] \quad (19)$$

where P_t^{grid} is the power purchase power of the power grid; c_t^{grid} is the unit price of power purchase from the power grid; $P_{i,t}^{\text{DG}}$ and c_i^{DG} are the plan and variable cost of conventional distributed power sources; $z_{i,t}^{\text{DR}}$ and $c_i^{\text{DR,cap}}$ are the capacity reserve of demand response (DR) resources (callable intraday) and its capacity fee; ΔY_{pc}^t is the system carbon emission deviation at time t ; γ_Y^t is the carbon trading price at time t ; and ω_f and ω_Y are the system cost weight and carbon trading cost weight, respectively.

(2) Second-stage objective: Economic correction under uncertainty

In the second stage, considering uncertainties such as wind and solar prediction deviations and load disturbances, a dynamic balance is achieved through energy storage, demand response, and power curtailment, with the goal of minimizing deviation correction costs:

$$f_2(x, y, \xi) = \sum_t \left[c^{\text{curt}} \sum_i p_{i,t}^{\text{curt}} + \sum_i c_i^{\text{DR}} \Delta L_{i,t}^{\text{DR,rt}} + \sum_i c_i^{\text{deg}} E_{i,t}^{\text{th}} + c^{\text{loss}} \sum_{\ell} r_{\ell} I_{\ell,t}^2 \right] \quad (20)$$

4.2. Uncertainty Modeling and Related Constraints

With the integration of high-proportion renewable energy, the operation of distribution networks features significant uncertainty. To ensure the economy and security of the system, robust optimization modeling is adopted, incorporating uncertainty sets and relevant constraints to render the scheduling scheme feasible even under the worst-case scenarios.

$$\begin{cases} p_{i,t}^{\text{RE}}(\xi) = \hat{p}_{i,t}^{\text{RE}} + \bar{u}_{i,t}^{\text{RE}} \\ |u_{i,t}^{\text{RE}}| \leq \bar{u}_{i,t}^{\text{RE}} \\ L_{i,t}(\xi) = \hat{L}_{i,t} + u_{i,t}^L \\ |u_{i,t}^L| \leq \bar{u}_{i,t}^L \\ \sum_{(i,t)} \left(\frac{|u_{i,t}^{\text{RE}}|}{\bar{u}_{i,t}^{\text{RE}}} + \frac{|u_{i,t}^L|}{\bar{u}_{i,t}^L} \right) \leq \Gamma \end{cases} \quad (21)$$

where $p_{i,t}^{\text{RE}}$ the renewable energy output at time t and node i considers the uncertainty disturbance ξ . $\hat{p}_{i,t}^{\text{RE}}$ is the predicted renewable energy output; $u_{i,t}^{\text{RE}}$, $u_{i,t}^L$ are the renewable energy prediction error and the load prediction error; $\bar{u}_{i,t}^{\text{RE}}$, $\bar{u}_{i,t}^L$ are the upper bounds of the renewable energy prediction error and the load prediction error; $\hat{L}_{i,t}$ is the predicted load demand; and Γ is the budget parameter, enabling the adjustable trade-off between robustness and economy.

With the increase in time, the operation efficiency of retired power battery energy storage and hydrogen energy storage decreases, and its carbon emission reduction effect also decreases. In order to more accurately calculate the carbon reduction effect of energy storage system at different moments in its life cycle, the improved moving weighted average method is used to convert the total carbon emissions of different energy storage life cycles into HECES daily carbon emissions, and then the HECES degree carbon emissions are obtained.

In this study, the results of the solution are moved forward by a time unit to deal with this problem. The improved formula can be expressed as follows:

$$\begin{cases} \bar{Y}'_{\text{RES},j} = \sum_{x=1}^s w_x Y_{\text{RES},j-x} \\ \varsigma_1 + \varsigma_2 + \varsigma_3 + \cdots + \varsigma_s = 1 \\ X = \sum_{x=1}^{s-1} (Y_{\text{RES},j-x} - Y_{\text{RES},j-x-1}) v_x \\ \alpha_j = \frac{\bar{Y}_{\text{RES},j+1} + \bar{Y}'_{\text{RES},j+1} + X}{2} \end{cases} \quad (22)$$

where $\bar{Y}'_{\text{RES},j}$ is the weighted average carbon emission, $\bar{Y}_{\text{RES},j}$ is the moving average carbon emission in a period, and s is the number of moving cycles of carbon emission data. ς_x is the weight of $Y_{\text{RES},j-x}$, $x = 1, 2, \dots, s$, v_x represents the weight difference between two adjacent carbon emission data, X represents the overall trend of carbon emission curve in s period, and α_j is the daily carbon emission weight coefficient.

According to the above steps, the carbon emissions generated by the full cycle carbon emissions and hydrogen energy storage of the retired power battery are converted into HECES daily carbon emissions. According to the daily charge and discharge of HECES,

the daily carbon emissions can be further converted into HECES kilowatt-hour carbon emissions, which can be expressed as:

$$Y_d^t = \tau_d \frac{\alpha_{\text{RES},t} Y_{\text{RES}} + \alpha_{\text{H},t} Y_{\text{H}}}{(1 + \kappa)^b c} \quad (23)$$

where Y_d^t is the HECES carbon emissions at time t ; $\alpha_{\text{RES},t}$, $\alpha_{\text{H},t}$ are the daily carbon emission weight coefficient of retired power battery and the daily carbon emission weight coefficient of hydrogen energy storage, respectively. κ , b , c , τ_d are carbon emission growth rate, system operation year, HECES daily charge and discharge times, and degree of carbon emission factor, respectively.

Similarly, the carbon emission quota of purchased electricity, wind power, and photovoltaic power can be expressed as:

$$\begin{cases} C_{\text{E,buy}}^t = \tau_{\text{E}} \frac{\alpha_{\text{buy},t} C_{\text{E,buy}}}{(1 + \kappa)^b P_{\text{E,buy}}^t} \\ C_{\text{WT}}^t = \tau_{\text{WT}} \frac{\alpha_{\text{WT},t} C_{\text{WT}}}{(1 + \kappa)^b P_{\text{WT},t}} \\ C_{\text{PV}}^t = \tau_{\text{PV}} \frac{\alpha_{\text{PV},t} C_{\text{PV}}}{(1 + \kappa)^b P_{\text{PV},t}} \end{cases} \quad (24)$$

where $C_{\text{E,buy}}^t$, C_{WT}^t , C_{PV}^t are external purchase of electricity, wind power, and photovoltaic carbon emission quotas at time t , respectively. τ_{E} , τ_{WT} , and τ_{PV} are the carbon emission factors of external power purchase, wind power, and photovoltaic power, respectively. $\alpha_{\text{buy},t}$, $\alpha_{\text{WT},t}$, $\alpha_{\text{PV},t}$ are the daily carbon emission weight coefficients of external power purchase, wind power, and photovoltaic power, respectively.

The system's carbon emission deviation is the difference between the carbon emission rights quota and the actual carbon emissions, which can be specifically expressed by the following formula:

$$\begin{cases} \Delta Y_{\text{pc}}^t = C_{\text{pe}}^t - Y_{\text{pf}}^t \\ C_{\text{pe}}^t = C_{\text{PV}}^t + C_{\text{WT}}^t + C_{\text{E,buy}}^t \\ Y_{\text{pf}}^t = Y_d^t + Y_{\text{load}}^t \end{cases} \quad (25)$$

where ΔY_{pc}^t is the system's carbon emission deviation at time t . C_{pe}^t , Y_{pf}^t are, respectively, the carbon emission rights quota and the actual carbon emissions at time t . Y_d^t is the carbon emissions of the hydrogen–electricity complementary energy storage system at time t . Y_{load}^t is the total carbon emissions of the load at time t .

Power balance (bus/system), node voltage constraints, branch power constraints:

$$\begin{cases} \sum_i p_{i,t}^{\text{net}} + P_t^{\text{grid}} = 0 \\ p_{i,t}^{\text{net}} = P_{i,t}^{\text{DG}} + P_{i,t}^{\text{dis}} + p_{i,t}^{\text{RE}}(\xi) - \left(L_{i,t}(\xi) - \Delta L_{i,t}^{\text{DR}} \right) - P_{i,t}^{\text{ch}} - P_{i,t}^{\text{curt}} \\ U_i^{\text{min}} \leq U_i \leq U_i^{\text{max}} \\ P_L^{\text{min}} \leq P_L \leq P_L^{\text{max}} \end{cases} \quad (26)$$

where U_i is the voltage amplitude of the i th node in the distribution network kV; U_i^{min} and U_i^{max} are, respectively, the lower limit and upper limit of the node voltage amplitude. P_L is the power transmitted by the L th line in the distribution network kW; P_L^{min} and P_L^{max} are, respectively, the lower limit and upper limit of the branch power.

Figure 3 shows the workflow of source–network–load–storage coordinated dispatching based on multi-scale robust optimization.

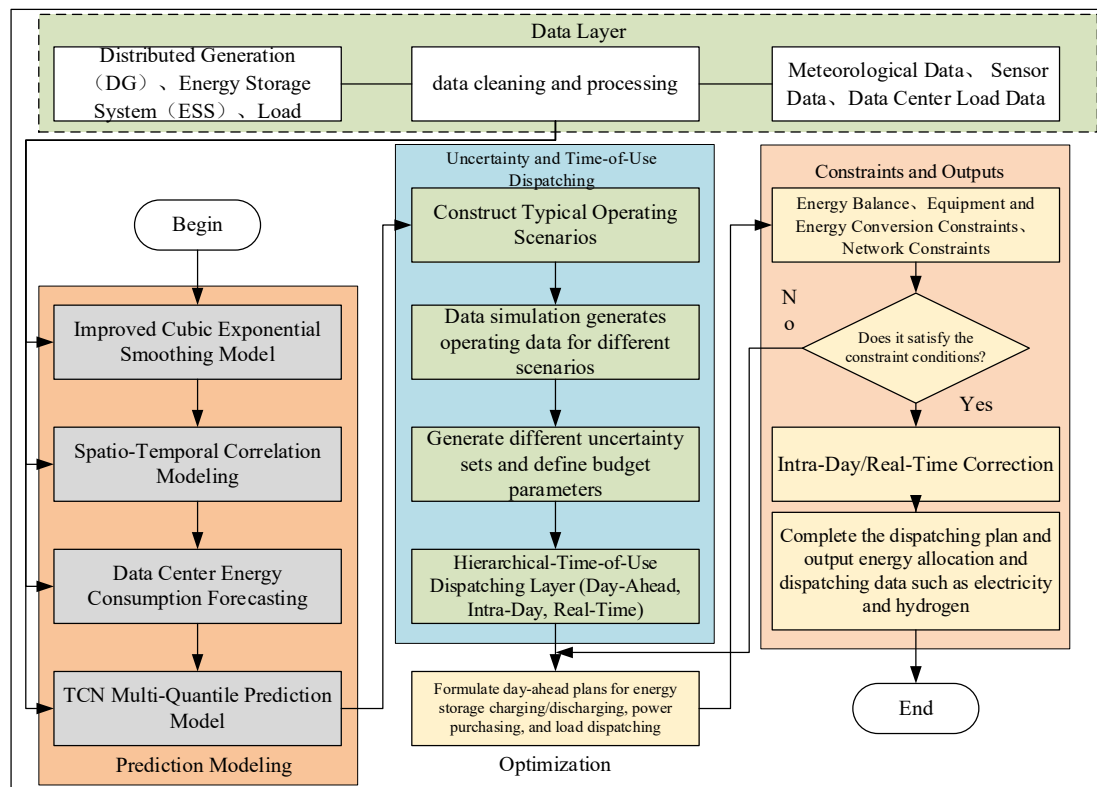


Figure 3. Multi-scale robust optimization framework for coordinated source–network–load–storage dispatch in distribution networks.

5. Case Study

5.1. Data Description

This paper selects a typical IEEE 33-bus distribution network as the case study object, with battery energy storage and hydrogen energy storage configured for case simulation. As a typical medium-voltage distribution system test model, the distribution network can fully reflect the impacts of distributed generation access and energy storage devices on power grid power flow distribution, voltage constraints, and operational economy [21,22]. The prediction curves are shown in Figure 4. In the IEEE 33-bus system, this paper arranges access points for photovoltaic power and wind power, respectively, and sets up multi-energy devices such as HST, HSD, and EL to form a source–grid–load–storage coupled architecture.

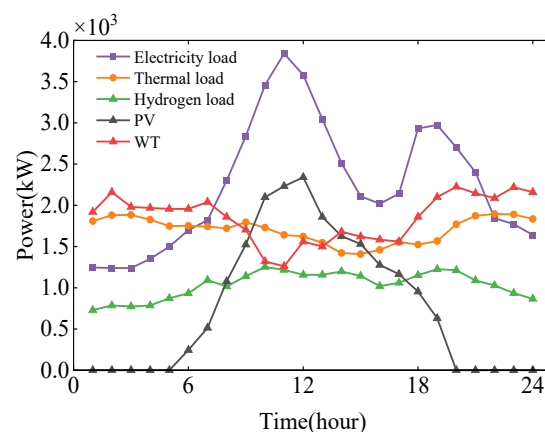


Figure 4. WT, PV, and load forecasting curves.

The operating parameters of each energy device are listed in Table 1, including energy storage capacity, maximum charging/discharging power, energy efficiency parameters, etc. To further analyze the mechanism of action of retired batteries and the hydrogen-electricity complementary system, this paper constructs three types of typical operating scenarios as shown in Table 2.

Table 1. Parameters of various energy equipment.

Name	Numerical Value	Name	Numerical Value
$P_{\max}^{\text{EB,E}}$	1000 kW	$P_{\max}^{\text{HB,H}}$	1200 kW
ζ_{etr}	87%	ζ_{htr}	95%
$E_{\text{RBES,max}}$	2200 kWh	$P_{\max}^{\text{RBES,cha}}, P_{\max}^{\text{RBES,dis}}$	400 kW
η_1	82%	η_0	85%
η_{HFC}	88%	$P_{\max}^{\text{HST,cha}}, P_{\max}^{\text{HST,dis}}$	450 kW
$P_{\max}^{\text{EL}}$	2500 kW	$P_{\max}^{\text{HFC}}$	2000 kW
η_{EL}	85%	I_{MJ}	142 MJ/kg

Table 2. Comparison table of different battery types and electricity–hydrogen interaction modes.

Scenario	Battery Types	Electric–Hydrogen Interaction Mode
1	brand-new battery	separate operation of electric energy storage and hydrogen energy storage
2	retired power batteries	separate operation of electric energy storage and hydrogen energy storage
3	retired power batteries	hydrogen–electric complementary energy storage system

5.2. Improvement in Prediction Accuracy Comparison

To verify the effectiveness of the intraday multi-time-scale hierarchical rolling dispatch strategy proposed in this paper, intraday dispatch is carried out based on Scenario 2 and Scenario 3 in the day-ahead dispatch. To meet the requirements of electricity, heat, and hydrogen load data for different intraday time scales, further refined prediction of electricity, heat, and hydrogen loads is performed based on the source–load data prediction model. The load prediction results are shown in Figure 5.

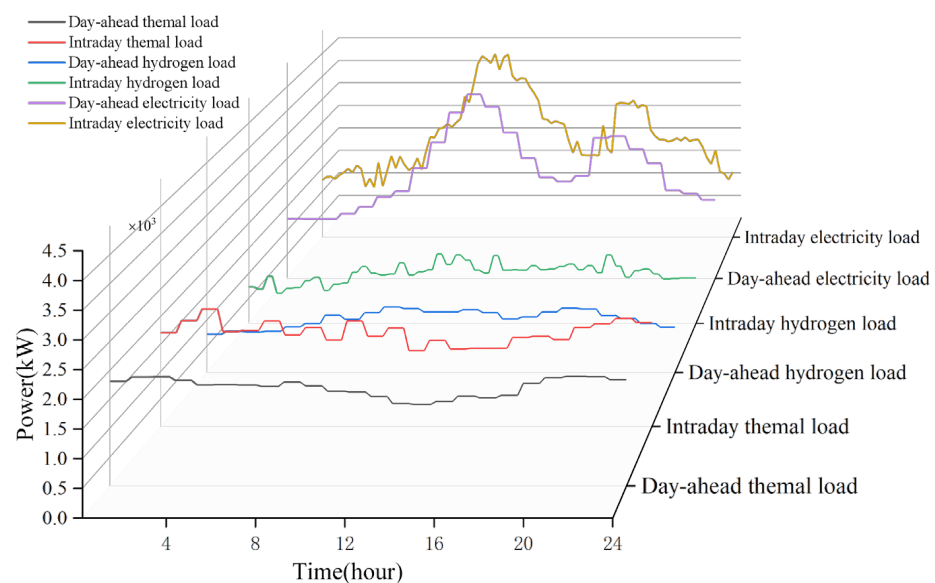


Figure 5. Day-ahead and intraday load forecast results for electricity, heat, and hydrogen.

As can be seen from Figure 5, intraday prediction can depict the ramping and declining characteristics during 7–12 h and 18–21 h more elaborately than day-ahead prediction: the rise and fall of electrical load during the midday peak period are captured earlier, with peak deviation converged; the depiction of the morning step and afternoon plateau of thermal load is smoother; and the overestimation/underestimation of short-term fluctuations in hydrogen load is corrected. Relying on higher time-frequency information, rolling optimization will synchronously adjust the output of coupled devices and energy purchase power. Under the refined prediction information, the adoption of multi-time-scale hierarchical rolling optimization dispatch results in more accurate intraday optimization outcomes for each load.

Figure 6 shows the influence of the number of adjacent stations K on the prediction performance. It can be seen that as K increases, the error decreases marginally, indicating that the moderate introduction of adjacent information can improve the robustness of the prediction, but the excessive neighborhood benefit is limited.

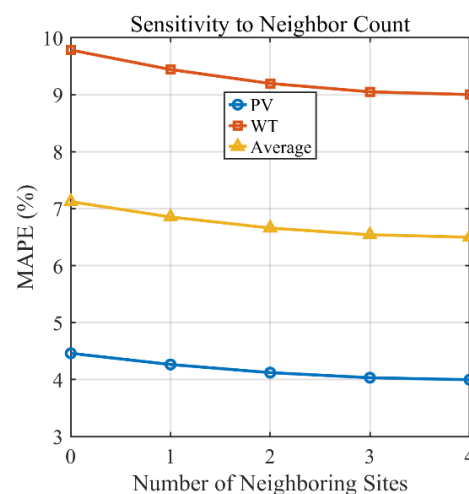


Figure 6. The influence of the number of adjacent stations K on the prediction performance.

Figure 7 shows the comparison of whether to introduce spatial correlation. The results show that after the introduction of spatial correlation, the electrical prediction error decreases more significantly, the MAPE decreases by about 22.2%, the photovoltaic error also improves by about 5.3%, and the comprehensive improvement is about 16.9%.

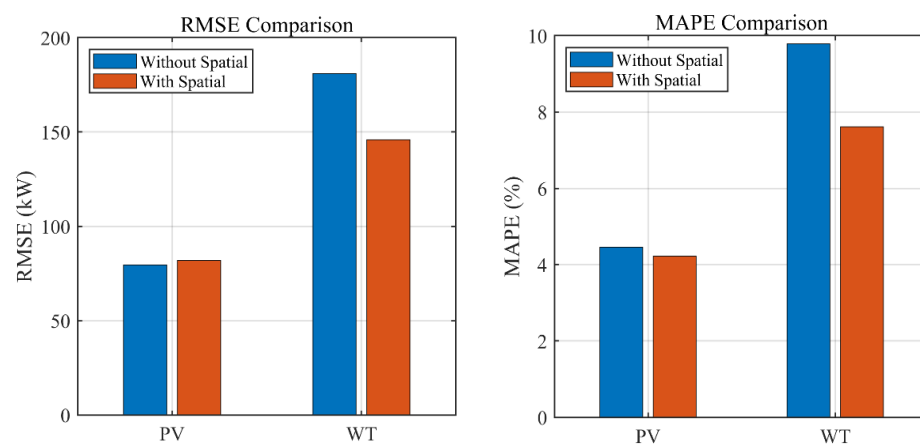


Figure 7. The influence of whether to introduce spatial correlation on prediction performance.

Figure 8 shows the proposed TCN probability prediction results and interval coverage verification. From the diagram, it can be seen that Q50 can better track the trend of output

change, and the 50% and 80% confidence intervals can effectively envelope the measured sequence; the coverage statistics show that the average coverage of the 50% interval is about 93.8%, and the coverage of the 80% interval reaches 100%, indicating that the quantile prediction and consistency constraints can provide an uncertainty description that can be used for robust scheduling.

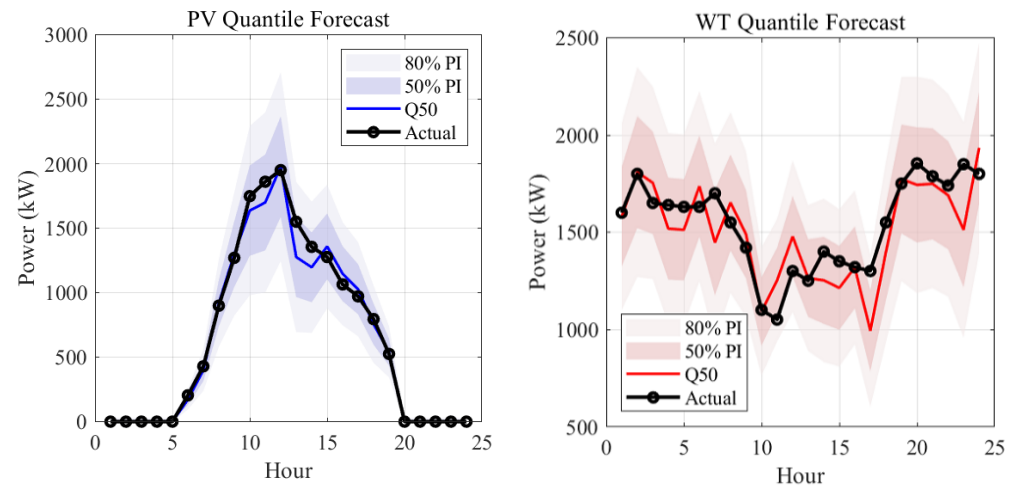


Figure 8. TCN probability prediction results and interval coverage.

As shown in Figure 9, by comparing with LSTM and other methods in terms of parameter quantity and inference speed, TCN has better comprehensive architecture performance.

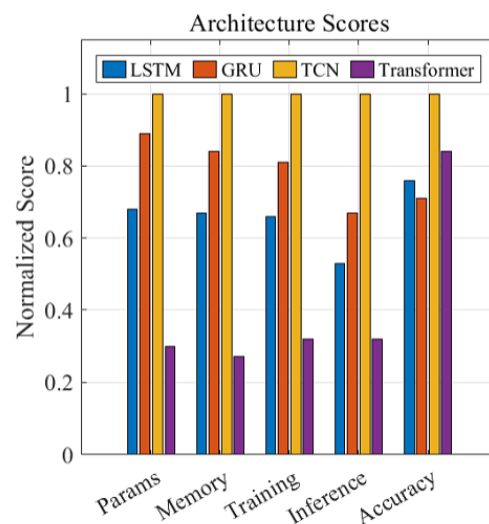


Figure 9. Compare TCN with other methods in terms of architecture performances.

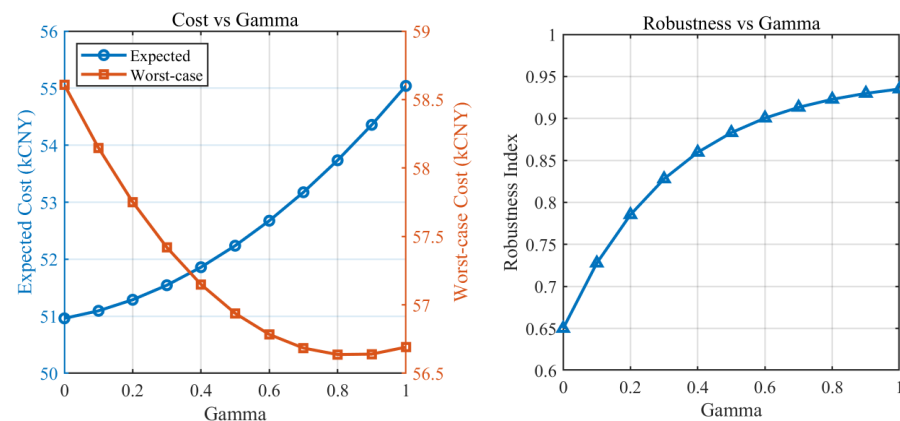
5.3. Analysis of Robust Optimization Effect

During the case operation, a two-stage robust optimization model is introduced in this paper to improve the stability and safety of dispatching. Through typical scenario generation and uncertainty set modeling, the model ensures feasibility under different operating conditions in the day-ahead stage. This enables the system to maintain power balance and voltage stability even with prediction deviations, thereby effectively reducing the risks of wind and solar curtailment and power supply interruption. The comparison of load loss rate cost and total operating cost under various scenarios is shown in Table 3, verifying the advantages of the proposed method in improving power supply reliability and economy.

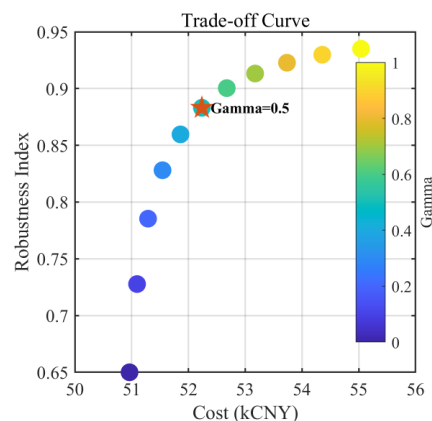
Table 3. Comparison of loss of load cost and total operating cost across different scenarios.

Scenario	Load Loss Rate Cost/10,000 Yuan	Total Operating Cost/10,000 Yuan	Energy Supply Reliability (p.u.)
1	15.41	48.96	0.93
2	12.35	45.34	0.96
3	10.35	47.34	0.98

In order to quantitatively describe the impact of the budget parameter Γ on the scheduling results, this paper scans $\Gamma \in [0, 1]$. The results are shown in Figure 10. With the increase in Γ , the worst-case cost decreases significantly and gradually tends to be stable, while the expected cost increases monotonously, reflecting the typical ‘economy–robustness’ trade-off relationship.

**Figure 10.** The relationship curve of Γ with cost and robustness.

Based on the above analysis, this paper selects $\Gamma = 0.5$ as the compromise point. As shown in Figure 11, the robustness is increased to 0.88 when the expected cost is only increased by about 2.5%, and the worst-case risk is significantly reduced.

**Figure 11.** Γ trade-off curve.

In order to verify the comparative advantages of the proposed two-stage robust optimization under different benchmark strategies, this paper sets up three methods of deterministic optimization, single-stage robustness, and two-stage robustness for comparison. As shown in Figure 12, the expected cost of the deterministic method is the lowest, but the worst-case cost increases significantly and the robustness is low. Single-stage robustness improves robustness, but at the expense of renewable consumption. The two-stage robustness achieves a comprehensive optimization between expected cost, worst-case cost,

and robustness and maintains a high level of renewable energy consumption, reflecting the structural advantage of day-ahead plan and intraday correction.

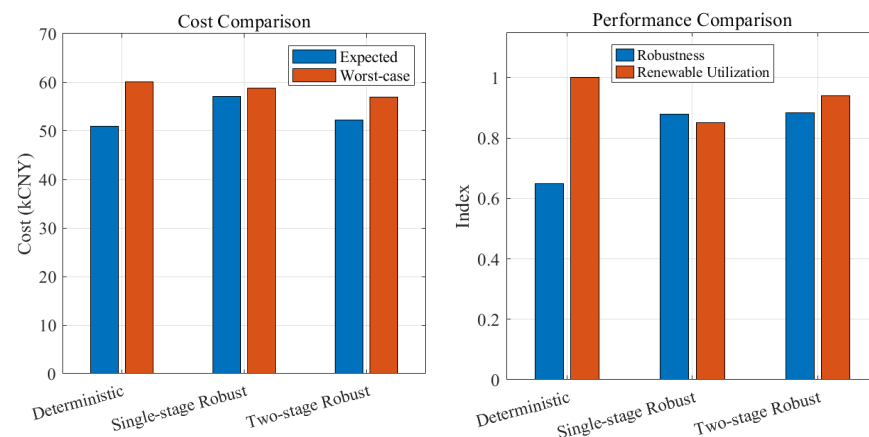


Figure 12. Comparison of benchmark methods.

The comparison of load loss rate cost and total operating cost under various scenarios is shown in Table 3, verifying the advantages of the proposed method in improving power supply reliability and economy.

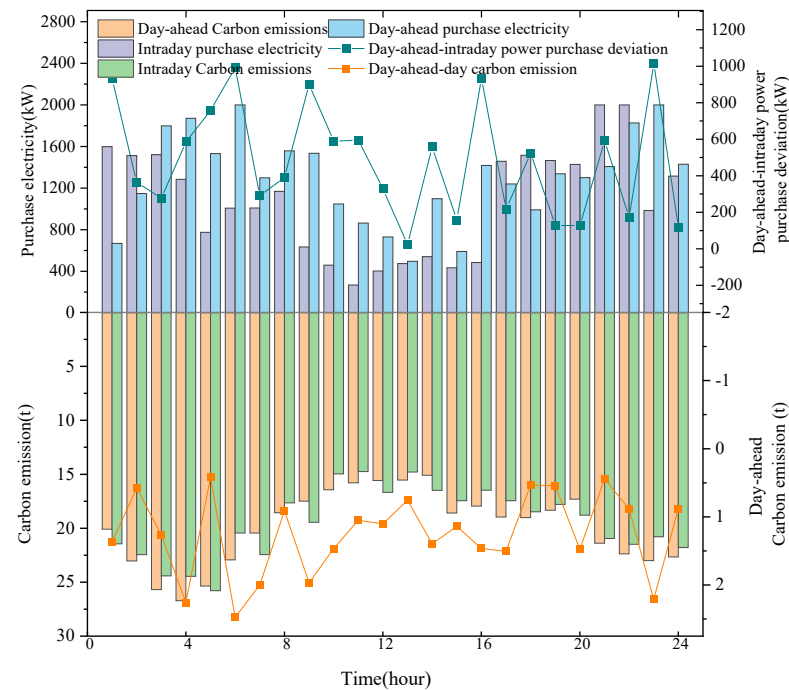
As can be seen from the results, the total operating cost and load loss rate cost of the three scenarios gradually decrease, indicating that different configuration schemes have improved the economy and power supply reliability of the system. In Scenario 1, the load loss cost accounts for 31.5% of the total cost, reflecting the insufficient adaptability of the system in the absence of hydrogen energy complementarity and retired batteries. After introducing retired batteries, the load loss cost drops to 27.2% and the total cost decreases, verifying the dual value of retired batteries. Scenario 3 further reduces the load loss cost to 21.9% through hydrogen–electric coupling. Although the total cost is slightly higher, the flexible regulation capacity of the system is significantly improved.

The comparison results of day-ahead and intraday electricity purchase as well as carbon emissions under Scenario 2 and Scenario 3 are shown in Figure 13.

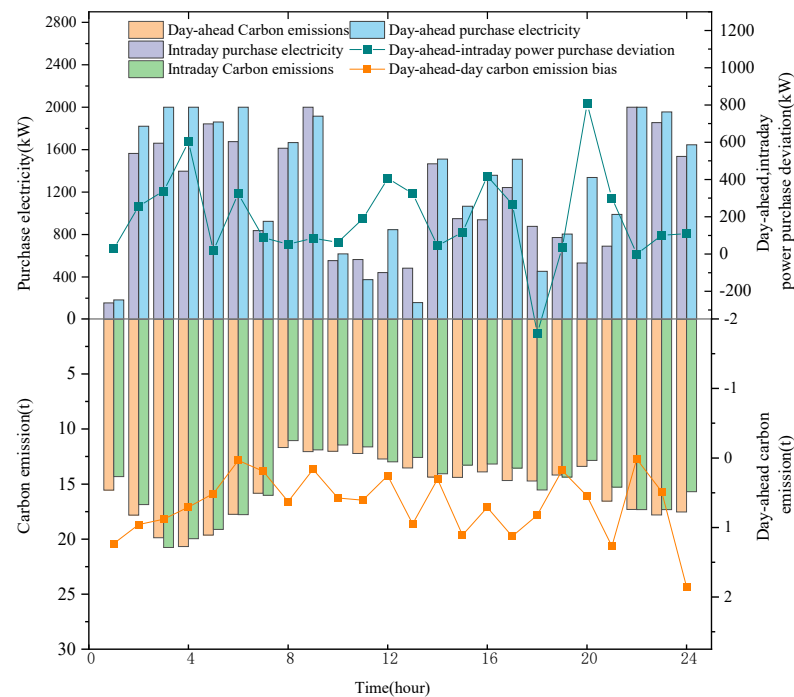
As shown in Figure 13, both Scenario 2 and Scenario 3 experienced fluctuations during the day-ahead-intraday power purchase process, but Scenario 2 was more significant, especially during the periods of 12:00–18:00 and 22:00–23:00, when the power purchase volume fluctuated by more than 20%. Due to the introduction of the hydrogen–electricity complementary energy storage system in Scenario 3, the deviation between the actual purchased electricity and the current plan has been significantly reduced, making the operation more economical and stable. In terms of carbon emissions, the total intraday emissions of both scenarios were lower than before. However, in Scenario 2, there was still an increase at 9:00 and 12:00, while in Scenario 3, the overall trend was downward, with the total intraday carbon emissions only decreasing by approximately 6% compared with before. This indicates that multi-time-scale coordinated dispatching can effectively enhance the low-carbon and economic efficiency of the distribution network.

Compared with Scenario 1, after the introduction of retired power batteries in Scenario 2, the total operating cost decreased from CNY 489,600 to CNY 453,400, a decrease of 7.39%, the cost of load loss rate decreased from CNY 154,100 to CNY 123,500, a decrease of 19.86%, and the reliability of energy supply increased from 0.93 to 0.96, indicating that retired batteries have a direct contribution to reducing costs and improving energy supply security. After the introduction of hydrogen–electricity complementation from Scenario 2 to Scenario 3, the cost of load loss rate is further reduced from CNY 123,500 to CNY 135,500, and the reliability is increased to 0.98. Although the total operating cost is

slightly increased by CNY 453,400 to 473,400, the flexibility and resilience of the system are significantly enhanced.



(a)



(b)

Figure 13. Day-ahead-intraday power purchase and carbon emissions results chart. (a) Scenario 2 day-ahead electricity purchase and carbon emission results; (b) Scenario 3 day-ahead, intraday power purchase and carbon emission results.

Further analysis shows that in the intraday and real-time phases, the second-stage robust mechanism can effectively deal with extreme situations and ensure feasibility and

reliability in the worst-case scenario. During the peak electricity price period from 12:00 to 18:00, the fluctuation range of power purchase in Scenario 3 was significantly smaller than that in Scenario 2. Compared with the day-before dispatching in Scenario 3, the energy purchase fluctuation rate of intraday dispatching decreased by 8.75%, which not only enhanced robustness but also reduced the cost of power loss and load loss rate, while also reducing carbon emissions and power curtailment rate. This indicates that two-stage robust optimization can not only suppress the impact of predictive uncertainty but also achieve reliable power supply and low-carbon economy, providing a strong guarantee for the distribution network in complex operating environments.

6. Conclusions

To achieve the economic operation of the distribution network side, the multi-scale source–grid–load–storage coordinated dispatching method proposed in this paper significantly improves system flexibility and robustness. Data-driven modeling enhances the accuracy of source and load forecasting, hierarchical and time-sharing optimization boosts economy and adaptability, and two-stage robust optimization ensures low-carbon and safe operation under uncertain conditions:

Under the framework of data-driven modeling and two-stage robust optimization, retired power batteries are introduced and coupled with hydrogen energy storage, which significantly realizes the cascade utilization value, reduces carbon emissions by approximately 10.7%, and lowers operating costs by 16.4%.

Through the hierarchical and time-sharing regulation architecture, the hydrogen–electric complementary energy storage system demonstrates greater flexibility and reliability during high-power load periods. Compared with traditional distribution networks, it features a lower load loss rate and stronger energy supply guarantee capability, with the load loss cost reduced to 21.9%.

The proposed multi-time-scale hierarchical rolling optimization dispatching strategy can flexibly adjust power purchasing capacity and mitigate power purchasing fluctuations. Compared with single-time-scale dispatching, the power purchasing volatility is reduced by 8.75%.

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