

Article

Two-Stage Distributed Robust Optimization Scheduling Considering Demand Response and Direct Purchase of Electricity by Large Consumers

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Abstract: The integration of large-scale wind power into power systems has exacerbated the challenges associated with peak load regulation. Concurrently, the ongoing advancement of electricity marketization reforms highlights the need to assess the impact of direct electricity procurement by large consumers on enhancing the flexibility of power systems. In this context, this paper introduces a Distributed Robust Optimal Scheduling (DROS) model, which addresses the uncertainties of wind power generation and direct electricity purchases by large consumers. Firstly, to mitigate the effects of wind power uncertainty on the power system, a first-order Markov chain model with interval characteristics is introduced. This approach effectively captures the temporal and variability aspects of wind power prediction errors. Secondly, building upon the day-ahead scenarios generated by the Markov chain, the model then formulates a data-driven optimization framework that spans from day-ahead to intra-day scheduling. In the day-ahead phase, the model leverages the price elasticity of the demand matrix to guide consumer behavior, with the primary objective of maximizing the total revenue of the wind farm. A robust scheduling strategy is developed, yielding an hourly scheduling plan for the day-ahead phase. This plan dynamically adjusts tariffs in the intra-day phase based on deviations in wind power output, thereby encouraging flexible user responses to the inherent uncertainty in wind power generation. Ultimately, the efficacy of the proposed DROS method is validated through extensive numerical simulations, demonstrating its potential to enhance the robustness and flexibility of power systems in the presence of significant wind power integration and market-driven direct electricity purchases.



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1. Introduction

With the proposal and implementation of China's "dual-carbon" strategy, a new type of power system characterized by a high proportion of new energy penetration is being constructed. Currently, the proportion of new energy generation, such as wind power, is increasing, marking significant attention to clean energy. Wind power, as a renewable and clean energy source, has become China's third major power source [1]. The rapid integration of renewable energy sources, particularly wind power, has introduced significant challenges to the stability and reliability of modern power systems. The intermittent and unpredictable nature of wind energy production necessitates advanced scheduling strategies to ensure efficient and economic grid operations. Furthermore, the evolving electricity market, with its increasing emphasis on direct electricity purchases by large consumers, adds another layer of complexity to power system management. These direct purchases can potentially

disrupt the balance between supply and demand, exacerbating the challenges associated with wind power integration [2].

In recent years, the continuous promotion of power market-oriented reform, and the large-scale implementation of direct electricity purchase by large users have provided new methods for power system peaking. Current research on large-user direct power purchases mainly focuses on transaction mode, risk management, cost sharing, and tariff models [3–10]. Ref. [3] proposes an optimal power purchase model for inter-provincial traders that takes into account the uncertainty risk of new energy output and load demand. Ref. [4] analyzes the metering method for direct power transmission prices for large users, breaking down transmission costs to reflect the risk of transmission line failure and fixed costs. Ref. [5] proposes a comprehensive fixed cost allocation method that considers three factors: time-of-use electricity prices, power quality, and direct power purchases. Refs. [6,7] comprehensively analyze the optimal strategy for large consumers to purchase electricity directly from the perspective of expected returns and risks. Ref. [8] proposes establishing a dynamic environmental economic dispatch model by considering direct power purchases by large users. Ref. [9] studies the electricity procurement strategy of large consumers in the electricity market. The proposed model can enable risk-averse strategies to control procurement costs within a certain range when the price of the electricity pool rises. Ref. [10] proposes a double auction model between competitive generators and large users in a bilateral electricity market that considers transmission costs. However, these studies have often overlooked the combined impact of large-scale wind power integration and direct power purchases on power system scheduling.

Some studies have proposed the implementation of a demand-side response (DR) to match new energy consumption [11]. Guiding users to adjust their consumption patterns through tariff guidance and incentive mechanisms not only realizes energy consumption but also provides flexibility for the grid. Studies [12] have analyzed time-sharing tariffs, real-time tariffs, and peak tariffs, highlighting the limitations of real-time tariffs in guiding responses and the uncertainty of peak tariff users' responses. Refs. [13,14] analyzed sequential electricity use, indicating that it facilitates load rescheduling during peak hours, achieves peak shaving and valley filling, and alleviates the pressure on electricity supply and demand. However, the effectiveness of a DR in the context of wind power integration and direct electricity purchases remains an area ripe for further exploration.

For the uncertainty brought by wind power, two main methods are used: stochastic optimization (SO) and robust optimization (RO). Refs. [15–18] state that stochastic programming relies on the estimation of the probability distribution, which is often difficult to obtain accurately, leading to significant estimation errors and requiring extensive numerical calculations; robust optimization often overemphasizes worst-case scenarios, limiting model performance under normal or favorable conditions. Given the multiple uncertainties in energy / transport demand and renewable energy, Ref. [19] adopts data-driven robust chance-constrained programming to effectively deal with the uncertainties in system operation and reduce the conservatism in traditional robust optimization. However, it does not discuss in depth the uncertainties in wind power forecasting and the role of DR strategies in the electricity market. In Ref. [20], the authors introduce a two-stage robust operational methodology catered to the complexities of integrated electrical–gas–thermal microgrids, taking into account non-homogeneous uncertainties. However, this study's purview does not encompass the synchronized optimization of the strategic direct procurement of electricity by large consumers. To overcome the limitations of SO and RO, some scholars have proposed a distributionally robust optimization (DRO) method [21]. DRO uses a fuzzy set of probability distributions to describe uncertain variables, seeking the worst probability distribution within a confidence set. By balancing robustness with economic benefits, DRO integrates the advantages of both SO and RO. In Refs. [22–24], the DRO method not only makes full use of the statistical information of the random variables but also ensures the robustness and economic efficiency of the optimization results. Ref. [25] can effectively solve a typical two-stage distributional robust optimization problem with discrete resources and

infinite support by evaluating the expected worst-case cost through the convex relaxation of non-convex and discrete-valued functions of resources. In contrast, the data-driven DRO is adept at leveraging the statistical nuances of historical data to simulate real-world scenarios, thereby accurately representing the uncertainty of wind power.

In the field of wind energy forecasting, accurately capturing the temporal dynamics and variability of wind speed is critical for generating reliable power output scenarios [26,27]. Ref. [28] proposes a data-driven MPC-ADP method that uses historical data for offline training to achieve uncertainty mitigation for real-time MEMG operation. However, this method requires a large amount of historical data for learning. Ref. [29] combines cluster analysis, daily characteristic index, and Markov chain to align generated scenarios with historical data's statistical laws closely. Ref. [30] superimposed the wind speed prediction error sequences generated by the ARMA model and Monte Carlo method onto the initial predicted wind speed to obtain the corresponding wind power output. However, these methods do not simultaneously consider the timing and interval characteristics of wind power uncertainty. In this paper, we introduce an enhancement to the conventional Markov chain model by devising a first-order Markov chain state transition matrix that incorporates interval-based properties. This innovative approach captures the stochastic nature of wind power variability across various temporal prediction horizons, thereby providing a more nuanced representation of uncertainty within the context of renewable energy forecasting.

In summary, in order to fully ensure the connection between the supply and demand sides of the power system and market-driven direct electricity purchases by large users, this paper proposes a novel joint optimization framework that combines the dynamics of source load storage with large-scale direct electricity procurement. A two-stage day-ahead intra-day multi-time-scale DROS scheduling method is constructed. Computational experiments using MATLAB/CPLEX validate the model's practical applicability and robustness in wind power integration. The main contributions are as follows:

- (1) Proposing a first-order Markov chain model with interval properties to address wind power forecasting uncertainty, considering temporal and interval characteristics of prediction errors.
- (2) Presenting an enhanced two-stage DR distributionally robust optimization model to mitigate wind power output volatility, aligning consumer behavior with wind farm revenue maximization and refining the approach with incentive signals for flexible wind power variability response.
- (3) Empirically validating the methodology through comparative analysis, demonstrating that the two-stage DR paradigm smoothens the load profile, reduces unit cycling, and curtails operational dispatch expenditure.

2. Wind Power Output Scenario Generation Model

Given the intrinsic stochasticity and variability of wind power, forecasts inherently encompass a margin of error. Thus, wind power output prognostication is conceptualized as the deterministic prediction augmented by a stochastic error component. This treatise undertakes an exhaustive examination of the prediction error's attributes to enhance the precision of wind power output delineation.

2.1. Analysis of Error Characteristics of Wind Power Prediction

In the realm of wind power forecasting, the predictions are typically close to the actual values, necessitating an in-depth investigation into the interplay between predictive estimates and their attendant inaccuracies. To this end, a scatter plot has been constructed utilizing a year's worth of historical data from a wind farm, as depicted in Figure 1a. Wind power generation demonstrates a pronounced serial correlation, reflecting a strong linkage between the outputs at consecutive time points. To substantiate the temporal correlation within wind power forecast errors, the Pearson correlation coefficients were meticulously

computed, resulting in the formulation of a correlation matrix that encapsulates the error's temporal dynamics, as depicted in Figure 1b.

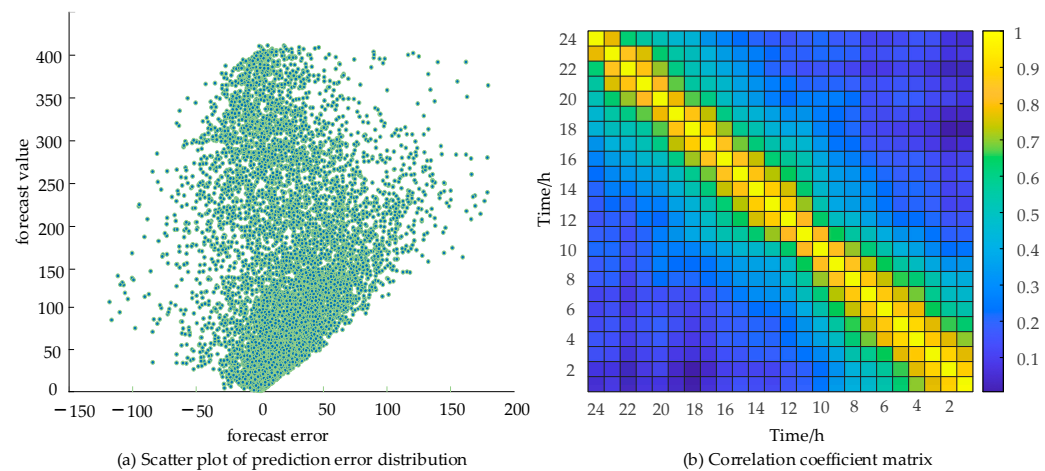


Figure 1. Error analysis chart for wind power forecasting: (a) scatter plot of prediction error distribution and (b) the correlation coefficient matrix.

In Figure 1, it is evident that the scatter plot graphically articulates several pronounced attributes of the prediction error in wind power output. Initially, the prediction error is observed to be distributed near the predicted values, conforming to an identifiable pattern, thereby highlighting the predictive value's influence on the prediction error. Subsequently, it becomes apparent that distinct predicted values manifest vastly different patterns of error distribution, with the overall distribution exhibiting a characteristic that is small at both ends and big in the middle profile.

In summary, when constructing the wind power output scenario set, we should fully consider the characteristics of the wind power prediction error in the interval and time sequence, i.e., different wind power prediction values have different prediction error distributions, and the prediction errors between neighboring moments have a strong correlation.

2.2. Fitting Probability Distribution of Wind Power Prediction Error

In the realm of distribution fitting, two predominant methodologies emerge: parametric and non-parametric estimation. Parametric estimation entails extracting specific parameters from sampled data to infer the overarching distribution, a process that, while systematic, may be impeded by the challenge of accurately defining the distribution, potentially leading to substantial inaccuracies. In contrast, non-parametric estimation eschews assumptions regarding the data's distributional form, opting instead for a data-driven approach that employs kernel density estimation or histogram techniques to approximate the probability density function. This flexibility renders non-parametric methods particularly adept at delineating the distributional nuances of data, particularly in scenarios where the distribution's contours are ambiguous or deviate from standard forms.

Therefore, in this paper, the wind power uncertainty is modeled and described using a non-parametric kernel density estimation with a probability density function $\hat{f}_h(\cdot)$ and a Gaussian kernel function $K(\cdot)$ as follows:

$$\hat{f}_h(E) = \frac{1}{nh} \sum_{q=1}^n K\left(\frac{E - E_q}{h}\right) \quad (1)$$

$$K\left(\frac{E - E_q}{h}\right) = \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{(E - E_q)^2}{2h^2}\right) \quad (2)$$

where E is the prediction error; E_q is the prediction error at time q ; h is the bandwidth; and n is the number of samples.

2.3. Improved Markov Chain Model

To enhance the precision in characterizing the temporal dynamics and interval properties of wind power output, this study introduces an innovative approach to the traditional first-order Markov chain model. This approach is distinguished by the incorporation of interval characteristics within the state transition matrix, establishing a methodological framework that is both robust and responsive to the nuances of wind power variability. By leveraging the distributional attributes embedded in historical data, the elbow method is applied to segment the data into M distinct classes. Subsequently, the model calculates the fitting functions pertinent to the forecast intervals alongside the state transition matrix PP that captures the probabilistic shifts between adjacent temporal states. This methodology results in a multi-state transfer Markov chain model endowed with heightened adaptability and fidelity to the empirical data. In the process of generating wind power scenarios for the day of interest, the predictive values are initially categorized according to the regions demarcated by the elbow method. Subsequently, the model selects the non-parametric kernel density estimation functions and the corresponding state transition matrices aligned with these classifications. Ultimately, these predictive values serve as the foundational reference for the subsequent sampling of prediction errors, ensuring data-driven and probabilistically coherent modeling of wind power output scenarios.

This innovation has endowed the model with exceptional performance when confronting the complexities of system modeling and analysis under diverse and fluctuating conditions, offering an enhanced analytical instrument for addressing real-world scenarios. The more precise representation of wind power output serves as a formidable underpinning for enhancing the predictive model's accuracy. A schematic depiction of the implementation process is delineated in Figure 2.

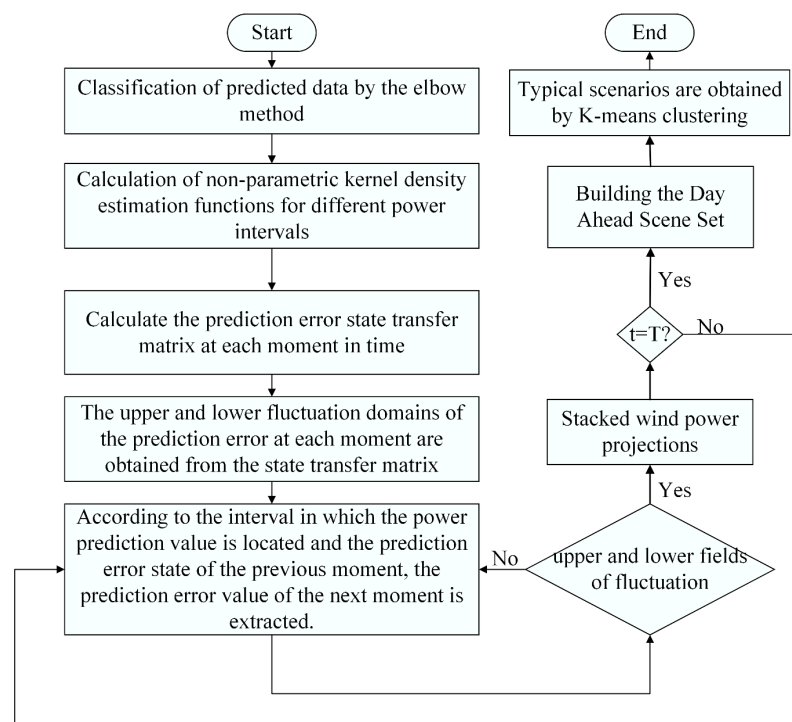


Figure 2. Day-ahead scene generation flowchart.

3. Demand Response Model

Load-side demand response (DR) resources can be categorized into two distinct types based on the mechanisms that elicit customer response: Price-based Demand Response (PDR) and Incentive-based Demand Response (IDR) [31]. PDR modulates electricity consumption patterns through various pricing strategies. These strategies include Time-Of-Use pricing (TOU), Real-Time Pricing (RTP), and Critical Peak Pricing (CPP), among others. IDR, conversely, is characterized by preferential policies formulated by the DR implementing agency to motivate users to respond to dispatch signals proactively. In the model presented in this paper, electricity pricing is structured around a Peak–Valley–Flat (PVF) segmented pricing mechanism. Furthermore, the model employs a price–demand elasticity matrix to quantify electricity DR.

3.1. Day-Ahead Demand Response Optimization Model

Incorporating a DR mechanism into the scheduling system is a strategic approach to synergistically optimize the allocation of energy resources, including generation sources, electrical loads, and storage systems. This optimization is achieved through dynamic load distribution adjustments. The dispatch center meticulously calibrates the tariff structure, leveraging load forecast data $P_{L,m}$ from the prior day. By strategically increasing the tariff during peak periods, the mechanism effectively reduces the load demand at these times. Conversely, reducing the tariff during the valley periods encourages an increase in load demand, thereby facilitating peak shaving and valley filling. This results in a smoothed load curve, denoted as $P'_{L,m}$. The refined load curve $P'_{L,m}$ serves as the foundational parameter for the subsequent day's scheduling plan, which includes the orchestration of thermal power generation units, wind farms, and energy storage systems.

In accordance with the methodology detailed in [32], the elasticity coefficient is formulated based on the electricity tariff's price–demand elasticity matrix. This relationship is mathematically articulated as follows (3):

$$e_{mn} = \frac{(P'_{L,m} - P_{L,m}) / P_{L,m}}{(\tau'_n - \tau_n) / \tau_n}, \begin{cases} e_{mn} \leq 0, m = n \\ e_{mn} \geq 0, m \neq n \end{cases} \quad (3)$$

where m and n denote discrete time moments within the analysis. The auto-elasticity coefficient, denoted as e_{mn} , is specifically applicable when $m = n$, reflecting the responsiveness of the electricity demand at a given moment to changes in its own price. Conversely, when $m \neq n$, the cross-elasticity coefficient, also represented by e_{mn} , captures the influence of price changes at one moment and the demand at a different moment.

The term $P_{L,m}$ refers to the original electricity load at time moment m prior to the implementation of any DR measures. Following the application of the DR, the adjusted electricity load at the same time moment m is denoted as $P'_{L,m}$. Similarly, τ_n symbolizes the original price of electricity at time moment n , while τ'_n indicates the revised price of electricity at time moment n after the DR measures have been enacted.

The price–demand elasticity matrix quantifies the impact of tariff changes on electricity demand under the PVF segmented tariff mechanism, as expressed in (4).

$$E = \begin{bmatrix} e_{ff} & e_{fp} & e_{fg} \\ e_{pf} & e_{pp} & e_{pg} \\ e_{gf} & e_{gp} & e_{gg} \end{bmatrix} \quad (4)$$

where f represents the peak period, p is the equal period, and g is the valley period.

When the DR is implemented, the change in load is shown in (5) as follows:

$$\begin{bmatrix} P'_{L,1} - P_{L,1} \\ P'_{L,2} - P_{L,2} \\ \vdots \\ P'_{L,t} - P_{L,t} \end{bmatrix} = \begin{bmatrix} P_{L,1} & & & \\ & P_{L,2} & & \\ & & \ddots & \\ & & & P_{L,t} \end{bmatrix} E \begin{bmatrix} (\tau'_1 - \tau_1)/\tau_1 \\ (\tau'_2 - \tau_2)/\tau_2 \\ \vdots \\ (\tau'_t - \tau_t)/\tau_t \end{bmatrix} \quad (5)$$

$$C_{\text{PDR}} = \sum_{t=1}^T (\tau_t P_{L,m} - \tau'_t P'_{L,m}) \quad (6)$$

The dispatch cost function for the day-ahead segmented tariff DR is defined in Equation (6), encapsulating the economic implications of the scheduling strategy within the DR mechanisms.

3.2. Within-Day Demand Response Optimisation Model

Given the stochastic and fluctuating nature of wind power generation, the short-term forecasts made a day before actual operation often diverge from the realized wind power output. This divergence can render the day-ahead scheduling plan inadequate to accommodate the within-day wind power variability, potentially leading to wind energy wastage and even jeopardizing the secure and stable operation of the power system. To address these issues, this study proposes a mechanism that incorporates the discrepancies between the intra-day ultra-short-term forecasted wind power output and the day-ahead scheduled wind power output into the electricity pricing structure. This approach aims to incentivize consumers to adjust their electricity consumption patterns and rectify the within-day deviations in wind power output through a secondary adjustment facilitated by the DR system.

The deviation between the within-day ultra-short-term wind power forecast output and the wind power day-ahead dispatch output is shown in (7) below.

$$\Delta P_{i,t}^w = P_{i,t}^{w0,n} - P_{i,t}^{w0,q} \quad (7)$$

where $P_{i,t}^{w0,n}$ and $P_{i,t}^{w0,q}$ are the intra-day ultra-short-term forecast output of wind farm i at moment t and the day-ahead dispatch output of wind power, respectively.

According to the theory of supply elasticity in economics, a coefficient θ is introduced to quantify the impact of the change in wind power forecast output on the tariff. This coefficient further guides load changes through tariff adjustments. The coefficient θ is shown in the following Equation (8).

$$\theta = \frac{\Delta P_{i,t}^w / \Delta P_{i,t}^{w0,q}}{\Delta \tau_n / \tau'_n} \quad (8)$$

where $\Delta \tau_n$ represents the variation in the wind power output deviation guidance tariff.

The guideline tariff for addressing within-day wind power deviations is shown in Equation (9) below.

$$\tau''_n = \tau'_n + \Delta \tau_n \quad (9)$$

Utilizing the day-ahead load profile as a foundational reference, a secondary load profile is generated under the revised tariff structure. This process integrates the demand-price elasticity coefficient to delineate the behavioral response of the participating customers to the new pricing scheme. The load after the within-day DR is shown in Equation (10) below.

$$P''_{L,m} = P'_{L,m} \left(1 + \varepsilon \frac{\Delta \tau'_n}{\tau'_n} \right) \quad (10)$$

$$C_{NPDR} = \sum_{t=1}^T (\tau'_n P'_{L,m} - \tau''_n P''_{L,m}) \quad (11)$$

The dispatch cost function that accounts for the within-day wind power output deviation and its guidance through the tariff DR is presented in Equation (11). This function is pivotal in quantifying the economic implications of the real-time adjustments necessitated by the variability of wind power generation.

4. Scheduling Model Framework

The scheduling framework is bifurcated into day-ahead and within-day phases, each serving a distinct purpose in the comprehensive management of energy resources. In the day-ahead phase, the scheduling center initiates the process by collecting load information and formulating a preliminary forecast curve based on the segmented tariff response expected from consumers. Utilizing this forecast curve, the center engages in tariff regulation aimed at optimizing load distribution through peak shaving and valley filling strategies. This simulation of load response results in an updated load prediction curve, which serves as the basis for issuing dispatch instructions to thermal power plants, wind farms, and energy storage facilities. Consequently, a dispatch plan for the subsequent day is developed. The within-day phase commences with an adjustment to the tariff, contingent upon the deviation of wind power output from the day-ahead forecast. Specifically, the tariff is lowered at times when the actual wind power output surpasses the forecasted levels and is raised in instances of underperformance. This adjustment is informed by the principle of supply elasticity, with the introduction of an elasticity coefficient that quantifies the extent of tariff fluctuation. This coefficient guides the formulation of a tariff that reflects the intra-day variability in wind power output. Subsequent to the establishment of the new tariff, consumers are prompted to adjust their electricity consumption patterns in response to the altered pricing structure. The magnitude of this load response is characterized by the demand–price elasticity coefficient, which reflects the sensitivity of demand to price changes. Based on the aggregated response from consumers, a new load forecast curve is derived. The dispatch center then issues a revised dispatch plan to thermal power plants, wind farms, and energy storage facilities, culminating in the development of an intra-day operation plan that accounts for real-time energy market dynamics. A two-phase demand response (DR) scheduling framework is shown in Figure 3.

4.1. Day-Ahead Scheduling Optimization Model

4.1.1. Day-Ahead Objective Function

In this study, an optimization model is meticulously constructed using a distributionally robust approach to examine the influence of various direct purchase tariffs on the integration of large-scale wind power into the power system. This model incorporates a multifaceted perspective, accounting for the nuances of power sales revenue, user-side DR, and operational expenditures. The initial stage of the model is based on a comprehensive consideration of a spectrum of wind power output forecast scenarios and the pivotal regulatory role of energy storage. This enables the formulation of a robust scheduling scheme for the day-ahead stage. To further refine the model's objectives, a penalty term for wind energy curtailment is incorporated into the objective function. This strategic addition aims to mitigate the incidence of wind curtailment and, in turn, enhance the overall utilization rate of wind power resources.

In summary, the objective function is shown in Equation (12).

$$\begin{aligned} \min C_1 = \min \left\{ \sum_{t=1}^T \left\{ \sum_{i=1}^{N_G} [C_{SS} + C_F + C_{SO2} + C_{CO2}] + C_t^s + C_{wind}^Q - E_H \right. \right. \\ \left. \left. - E_{wind} + C_{PDR} + \max_{\{p_k\} \in \Omega} \left\{ \sum_{k=1}^K P_k \min \left\{ \sum_{i=1}^{N_G} C_H + \sum_{i=1}^{N_W} C_W \right\} \right\} \right\} \right\} \quad (12) \end{aligned}$$

where T is the total number of time periods; N_G is the number of thermal power units; P_k is the probability of the k th scenario; Ω is the feasible domain of the real-time operation scenario; K is the number of scenes; N_W is the number of wind farms; and C_{PDR} is the demand response dispatch cost function for the recent segmented electricity price, as shown in Equation (6).

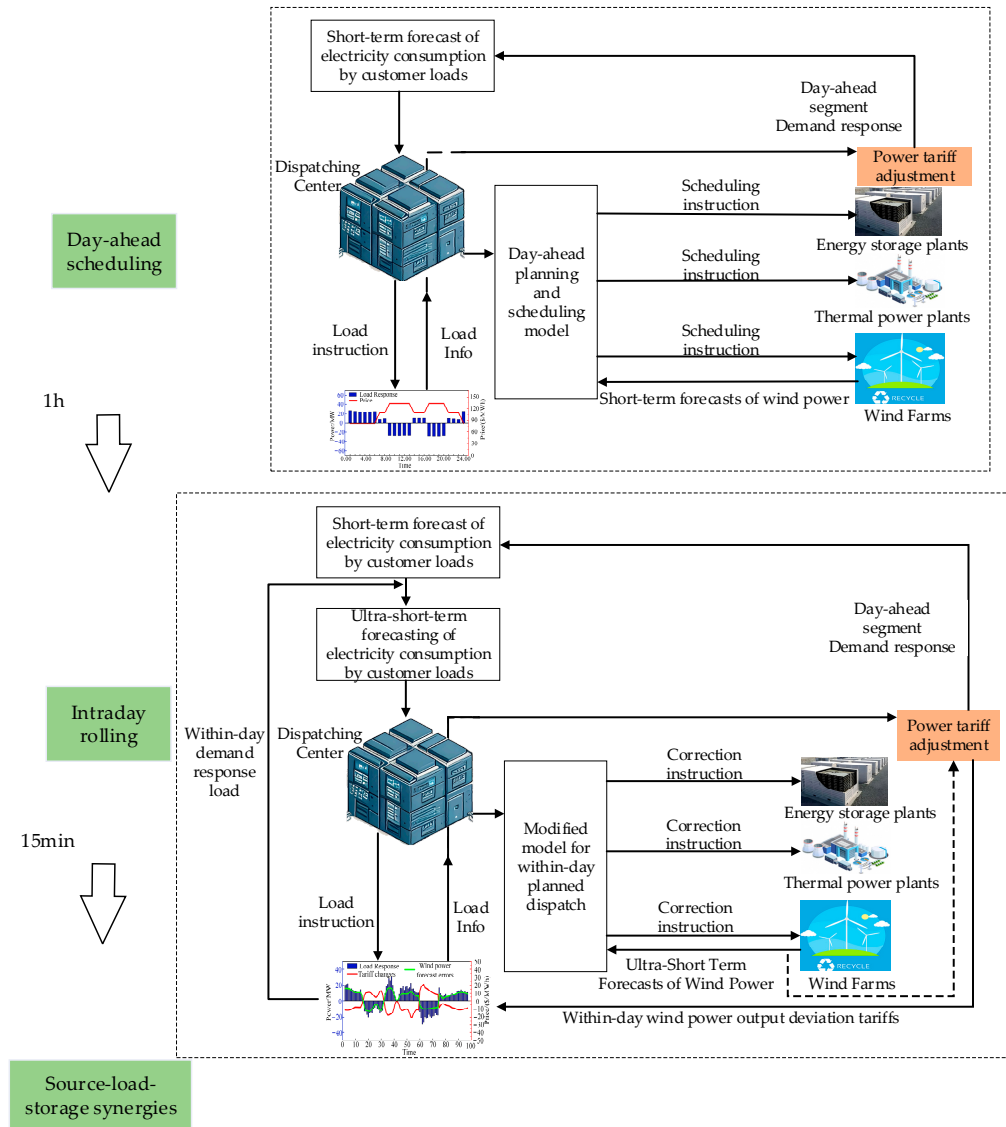


Figure 3. A two-phase demand response (DR) scheduling framework.

The start-up and shutdown cost of the thermal power unit i at time t is as follows (13).

$$C_{SS} = S_{Ti}y_{i,t} + S_{Di}Z_{i,t} \quad (13)$$

In the formula, S_{Ti} and S_{Di} are the start-up and shutdown costs of thermal power unit i at time t and $y_{i,t}$ and $Z_{i,t}$ are the on-off state parameters of thermal power unit i at time t . The fuel cost of thermal unit i at moment t is given in Equation (14) below.

$$C_F = a_i P_{i,t}^2 + b_i P_{i,t} + c_i U_{i,t} \quad (14)$$

In the formula, $U_{i,t}$ is the state parameter of thermal power unit i at time t ; a_i , b_i , c_i are the power generation cost coefficients of thermal power unit i ; and $P_{i,t}$ is the active power output of thermal power unit i at time t .

The environmental cost of CO₂ for thermal unit i at moment t is given in Equation (15) below.

$$C_{CO_2} = \gamma_{en,c} [\alpha_{c,i} P_{i,t}^2 + \beta_{c,i} P_{i,t} + \lambda_{c,i} U_{i,t}] \quad (15)$$

In the formula, $\gamma_{en,c}$ is the environmental cost coefficient of CO₂ released by combustion and $\alpha_{c,i}$, $\beta_{c,i}$ and $\lambda_{c,i}$ are the CO₂ emission coefficients of thermal power unit i .

The environmental cost of SO₂ for thermal unit i at moment t is given in Equation (16) below.

$$C_{SO_2} = \gamma_{en,s} [\alpha_{s,i} P_{i,t}^2 + \beta_{s,i} P_{i,t} + \lambda_{s,i} U_{i,t}] \quad (16)$$

In the formula, $\gamma_{en,s}$ is the environmental cost coefficient of SO₂ released by combustion and $\alpha_{s,i}$, $\beta_{s,i}$ and $\lambda_{s,i}$ are the SO₂ emission coefficients of thermal power unit i .

When considering the operating cost of battery storage equipment, both the initial investment cost and the operation and maintenance costs must be included. During time period t within the payback period, the average operating cost is calculated as follows (17).

$$C_t^s = \sum_{s=1}^{N_s} K_s [\eta_s^{\text{ch}} p_{s,t}^{\text{ch}} + p_{s,t}^{\text{dis}} / \eta_s^{\text{dis}}] \quad (17)$$

In the formula, N_s is the total number of energy storage elements; K_s is the unit charge and discharge cost of the energy storage element S after conversion; $p_{s,t}^{\text{ch}}$ and $p_{s,t}^{\text{dis}}$ are the charge and discharge power of the energy storage element S , respectively, and η_s^{ch} and η_s^{dis} are the charge-discharge efficiency of the energy storage element S , respectively.

The cost of wind abandonment penalties for wind farms is given in Equation (18) below.

$$C_{\text{wind}}^Q = \delta \sum_{i=1}^{N_W} (P_{i,t}^{\text{w}0} - P_{i,t}^{\text{w}1}) \quad (18)$$

In the formula, δ is the penalty coefficient of abandoning wind; $P_{i,t}^{\text{w}0}$ is the predicted output value of wind farm i at time t ; and $P_{i,t}^{\text{w}1}$ is the actual dispatching output of wind farm i at time t .

The total revenue from the sale of electricity of the thermal power unit at moment t is given in Equation (19) below.

$$E_H = \sum_{i=1}^{N_G} \gamma_i^s P_{i,t}^s + \gamma_i^z P_{i,t}^z \quad (19)$$

In the formula, γ_i^s is the electricity selling price to the grid at time t ; γ_i^z is the direct purchase price at time t ; $P_{i,t}^s$ is the non-direct purchase power of thermal power unit i at time t ; and $P_{i,t}^z$ is the direct purchase power of thermal power unit i at time t .

The total revenue from the sale of electricity from the wind farm is given in Equation (20) below.

$$E_{\text{wind}} = \sum_{i=1}^{N_W} \gamma_i^s P_{i,t}^{\text{w}} \quad (20)$$

The cost of thermal unit output adjustment is given in Equation (21) below.

$$C_H = d_{i,t} \Delta P_{i,t,k} \quad (21)$$

In the formula, $d_{i,t}$ is the output adjustment cost coefficient of the thermal power unit i at time t and $\Delta P_{i,t,k}$ is the output adjustment of thermal power unit i at time t .

The cost of the difference in wind power output a few days ago is as follows in Equation (22).

$$C_W = c_{\text{wind}} (P_{i,t,k}^{w0} - P_{i,t,k}^w) \quad (22)$$

In the formula, c_{wind} is the output adjustment cost of wind farm i at time t .

4.1.2. Day-Ahead Restrictive Condition

1. Power balance constraints

$$\sum_{i=1}^{N_G} P_{i,t}^q + \sum_{s=1}^{N_s} \eta_s^{\text{ch}} P_{s,t}^{\text{ch},q} + \sum_{s=1}^{N_s} P_{s,t}^{\text{dis},q} / \eta_s^{\text{dis}} + \sum_{i=1}^{N_W} P_{i,t}^{w0,q} = P'_{L,m} \quad (23)$$

where $P'_{L,m}$ is the total load of the system at time t .

2. Thermal unit output constraints

$$P_i^{\min} U_{i,t} \leq P_{i,t} \leq P_i^{\max} U_{i,t} \quad (24)$$

where $P_i^{\max}$ and $P_i^{\min}$ are the maximum and minimum values of thermal unit i output.

3. Crew climbing constraints

$$-R_i^{\text{down}} \Delta T \leq P_{i,t} - P_{i,t-1} \leq R_i^{\text{up}} \Delta T \quad (25)$$

where R_i^{up} and R_i^{down} are the up and down climbing rate of unit i . ΔT is the climbing time.

4. Minimum start/stop time constraint for the unit

$$\begin{cases} T_i^{\text{on}} \geq T_i^U \\ T_i^{\text{off}} \geq T_i^D \end{cases} \quad (26)$$

where T_i^{on} and T_i^{off} are the continuous starting and stopping time of the unit i and T_i^U and T_i^D are the minimum starting and stopping time of the unit i .

5. Alternative constraints

$$\sum_{i \in I} P_i^{\max} U_{i,t} \geq (1 + R) P_{L,f,t} \quad (27)$$

where R is the standby rate.

6. Contractual electricity constraints in direct purchase agreements

$$\sum_{t=1}^T P_{i,t}^z = E_i \quad (28)$$

where E_i is the daily direct purchase of electricity signed by unit i .

7. Real-time wind power output constraints

$$0 \leq P_{i,t}^w \leq P_{i,t}^{w0} \quad (29)$$

8. Demand response constraints

$$\Delta P_{L,m}^f + \Delta P_{L,m}^p + \Delta P_{L,m}^g = 0 \quad (30)$$

$$\begin{cases} -\lambda P_{L,m}^{f,0} \leq P_{L,m}^f \leq \lambda P_{L,m}^{f,0} \\ -\lambda P_{L,m}^{p,0} \leq P_{L,m}^p \leq \lambda P_{L,m}^{p,0} \\ -\lambda P_{L,m}^{g,0} \leq P_{L,m}^g \leq \lambda P_{L,m}^{g,0} \end{cases} \quad (31)$$

$$-\beta P_{L,m} \leq \Delta P_{L,m} \leq \beta P_{L,m} \quad (32)$$

where $\Delta P_{L,m}^f$, $\Delta P_{L,m}^p$, and $\Delta P_{L,m}^g$ are the load changes after the DR at peak, level, and valley moments, respectively; $\Delta P_{L,m}^{f0}$, $\Delta P_{L,m}^{p0}$, $\Delta P_{L,m}^{g0}$ are the original electricity loads at peak, level, and valley moments, respectively; $\Delta P_{L,m}$ is the load change at m moments after the DR a few days ago; and λ and β are the total transfer limit and the transfer limit at a certain moment in the process of electricity load transfer, respectively, and the value of the transfer limit is taken as 0.2.

9. Energy storage constraints

$$0 \leq p_t^{dis} \leq U_{s,t} P_s^{\max} \quad (33)$$

$$0 \leq p_t^{ch} \leq [1 - U_{s,t}] P_s^{\max} \quad (34)$$

$$\eta \sum_{t=1}^{24} p_t^{ch} - \frac{1}{\eta} \sum_{t=1}^{24} p_t^{dis} = 0 \quad (35)$$

$$E_s^{\min} \leq E_s(0) + \eta \sum_{t=1}^T p_t^{ch} - \frac{1}{\eta} \sum_{t=1}^T p_t^{dis} \leq E_s^{\max} \quad (36)$$

where $P_s^{\max}$ is the maximum permissible charging and discharging power of the energy storage; $U_{s,t}$ is the state of charging and discharging, 1 means discharging and 0 means charging; $E_s(0)$ is the capacity of the energy storage at the initial moment; and $E_s^{\max}$ and $E_s^{\min}$ are the upper and lower limits of the residual capacity of the energy storage in the scheduling process.

4.2. Within-Day Scheduling Optimization Model

In the within-day scheduling stage, this study employs a prediction scale of 4 h within a day and a rolling scale of 15 min to forecast and adjust the electricity load transfer. Ensuring the safe and stable operation of the power system, the model comprehensively accounts for the prediction error of wind power output. Using the deviation of wind power output to guide the dynamic tariff adjustments, the model aims to achieve real-time optimization of the load curve.

4.2.1. Within-Day Objective Function

Building upon the day-ahead phase of the scheduling plan, the within-day phase adeptly addresses the inherent uncertainty of wind power output by dynamically adjusting the PDR load call profiles within the region. The objective function of this phase is meticulously designed to minimize the cost associated with these adjustments, thereby optimizing the operational efficiency of the power system in the face of fluctuating wind energy resources, as shown in Equation (37).

$$\min \left\{ \sum_{t=1}^T \sum_{i=1}^{N_W} \delta^n |\Delta P_{i,t}^w| + \sum_{t=1}^T C_d + \sum_{t=1}^T C_s + C_{NPDR} \right\} \quad (37)$$

where δ^n is the intra-day wind abandonment penalty factor; C_d is the intra-day unit adjustment cost and C_s is the intra-day storage adjustment cost; and C_{NPDR} is the demand response dispatch cost function for the guide price of wind power output deviation within the day, as shown in Equation (11).

The total adjustment cost of the intra-day unit is shown in Equation (38).

$$C_d = d'_{i,t} \Delta P'_{i,t,k} \quad (38)$$

where $d'_{i,t}$ is the output adjustment cost of thermal unit i at moment t during the intra-day dispatch phase and $\Delta P'_{i,t,k}$ is the output adjustment of thermal unit i at moment t during the intra-day dispatch phase.

The total adjustment cost of intra-day energy storage is shown in Equation (39).

$$C_s = d'_{s,t} \Delta P'_{s,t} \quad (39)$$

where $d'_{s,t}$ is the output adjustment cost of storage s at moment t in the intra-day dispatch phase and $\Delta P'_{s,t}$ is the output adjustment of storage s at moment t in the intra-day dispatch phase.

4.2.2. Within-Day Restrictive Condition

The constraints are essentially identical to those in the day-ahead scheduling optimization model. The primary additions include price adjustment constraints and power balance constraints.

1. Price adjustment constraints

$$\begin{cases} m^{\text{marg}} \leq m^g \leq m^p \leq m \\ m^g \leq m^0 \leq m^f \\ k_1 \leq m^f / m^g \leq k_2 \end{cases} \quad (40)$$

where m^{marg} is the generation cost; m^f , m^p , m^g are the peak, level, and valley tariffs after changing the tariffs, respectively; m^0 is the original tariff; and k_1 and k_2 are the peak-to-valley tariff ratios, which are taken as $k_1 = 2$ and $k_2 = 5$.

2. Power balance constraints

$$\sum_{i=1}^{N_G} P_{i,t}^n + \sum_{s=1}^{N_s} \eta_s^{\text{ch}} P_{s,t}^{\text{ch},n} + \sum_{s=1}^{N_s} P_{s,t}^{\text{dis},n} / \eta_s^{\text{dis}} + \sum_{i=1}^{N_W} P_{i,t}^{\text{w}1*} = P_{L,t}'' \quad (41)$$

where $P_{i,t}^n$ is the intra-day active output of thermal power unit i at moment t ; $P_{s,t}^{\text{ch},n}$ is the intra-day discharge power of energy storage element S at moment t ; and $P_{s,t}^{\text{dis},n}$ is the intra-day charging power of energy storage element S at moment t .

5. Comprehensive Paradigm Constraints

This paper introduces a synergistic efficiency optimization scheduling model for source-load-storage systems, incorporating a two-stage DR framework and the direct purchase of electricity by large consumers. The model is designed to address the challenge of wind power output uncertainty. The objective is to maximize the expected value of the objective function across various demand scenarios; however, identifying the actual probability distribution is often elusive. To reconcile the discrepancy between the theoretical and empirical probability distributions and ensure that the derived distribution aligns closely with actual operational data without deviating significantly from real-world conditions, this study employs an innovative approach. It uses the initial probability distribution of each discrete scenario as a reference point. Furthermore, it refines the probability distribution of wind power scenarios by applying constraints through the L1 norm and the ∞ paradigm in tandem, as shown in Equation (42).

$$\Omega = \left\{ \{P_k\} \left| \begin{array}{l} P_k \geq 0, k = 1, 2, \dots, K \\ \sum_{k=1}^K P_k = 1 \\ \sum_{k=1}^K |P_k - P_k^o| \leq \theta_1 \\ \max_{1 \leq k \leq K} |P_k - P_k^o| \leq \theta_\infty \end{array} \right. \right\} \quad (42)$$

where P_k^o is the initial probability value of the k th scene and θ_1 and θ_∞ are the maximum allowable deviation values for L1 norm and L-infinity norm, respectively.

According to the literature [33,34], the confidence level of $\{P_k\}$ is shown in Equation (43) as follows:

$$\begin{cases} \Pr\left\{\sum_{k=1}^K |P_k - P_k^o| \leq \theta_1\right\} \geq 1 - 2Ke^{-\frac{2M\theta_1}{K}} \\ \Pr\left\{\max_{1 \leq k \leq K} |P_k - P_k^o| \leq \theta_\infty\right\} \geq 1 - 2Ke^{-2M\theta_\infty} \end{cases} \quad (43)$$

Let the right-hand side of the above inequality be the confidence level α_1 and α_∞ of the probability distribution values, respectively; then, Equation (43) can be transformed into Equation (44) as follows:

$$\begin{cases} \Pr\left\{\sum_{k=1}^K |P_k - P_k^o| \leq \theta_1\right\} \geq \alpha_1 \\ \Pr\left\{\max_{1 \leq k \leq K} |P_k - P_k^o| \leq \theta_\infty\right\} \geq \alpha_\infty \end{cases} \quad (44)$$

Equations (43)–(45) can be obtained as follows:

$$\begin{cases} \theta_1 = \frac{K}{2M} \ln \frac{2K}{1-\alpha_1} \\ \theta_\infty = \frac{1}{2M} \ln \frac{2K}{1-\alpha_\infty} \end{cases} \quad (45)$$

Equations (12)–(45) are the two-stage DRO model proposed in this paper.

6. DRO Model Solving

To solve the day-ahead DR model as articulated in Equation (12), this study employs the Column-and-Constraint Generation (CCG) algorithm. The procedural steps of the CCG algorithm, as applied to this model, are outlined below.

To enhance computational tractability, the two-stage model introduced in this paper is decomposed into a master problem and a set of sub-problems. The CCG algorithm is applied, iteratively solving both the master and sub-problems in a cyclical manner. This iterative process converges towards identifying the optimal solution for the original problem formulation. The master problem is mathematically represented in the following Equation:

$$\min_{x \in X, y_0 \in Y(x, \xi_0), y_k^{(m)} \in Y(x, \xi_k), \eta} a^T x + b^T y_0 + c^T \xi_0 + \eta \quad (46)$$

$$\eta \geq \sum_{k=1}^K P_k^{(m)} (b^T y_k^{(m)} + c^T \xi_k), \forall m = 1, 2, \dots, n \quad (47)$$

where x is the first-stage robust decision variable; y_k is the second-stage variable in the k th scenario; ξ_0 is the predicted value of wind power output; ξ_k is the value of wind power output in the k th scenario; and m is the number of iterations.

The form of the sub-problem is as follows (48):

$$\max_{\{p_k\} \in \Omega} \sum_{k=1}^K P_k \min_{y_k \in Y(x^*, \xi_k)} (b^T y_k + c^T \xi_k) \quad (48)$$

From the sub-problem in Equation (48), the scenario problems are independent of each other in the inner min function, which can be solved in parallel to speed up the solution and are denoted as $f(x^*, \xi_k)$, so the sub-problem can be modified with Equation (49) as follows:

$$\eta(x^*) = \max_{\{p_k\} \in \Omega} \sum_{k=1}^K f(x^*, \xi_k) P_k \quad (49)$$

Since the constraints in Equation (42) involve absolute values, this paper introduces two binary auxiliary variables to convert them into linear constraints. The specific solution process is detailed as follows.

The absolute value term in Equation (43) represents the upper and lower bounds of the integrated paradigm constraints; however, it cannot be directly used to solve the linear objective function in Equation (12). Since the probability P_k has a unique probability offset with respect to P_k^0 , the positive and negative offsets of the probability P_k with respect to P_k^0 are distinguished by the introduction of the 0–1 auxiliary variables Z_k^+ and Z_k^- , so the process of dealing with the absolute value term of the 1 parameter is as follows:

$$Z_k^+ + Z_k^- \leq 1, \forall k \quad (50)$$

In addition, the following constraints need to be satisfied:

$$\begin{cases} 0 \leq P_k^+ \leq Z_k^+ \theta_1, \forall k \\ 0 \leq P_k^- \leq Z_k^- \theta_1, \forall k \\ P_k = P_k^0 + P_k^+ - P_k^-, \forall k \end{cases} \quad (51)$$

Thus, Equation (44) can be equivalently expressed as follows:

$$\sum_{k=1}^K P_k^+ + P_k^- \leq \theta_1 \quad (52)$$

The treatment of absolute value terms for the L-infinity norm follows the same procedure as for the L1 norm, distinguishing positive and negative offsets by introducing the constraints in Equations (50) and (51), which differ from Equation (52) for the L1 norm in that the following constraints need to be added:

$$P_k^+ + P_k^- \leq \theta_\infty, \forall k \quad (53)$$

Consequently, the model in Equation (12) is skillfully transformed into a mixed-integer linear programming (MILP) problem. This transformation is pivotal, as it enables the efficient determination of the worst-case probability distribution, denoted as P^* . The identified probability distribution P^* is then relayed to the master problem, where it is employed in an iterative solution process aimed at achieving an optimal solution.

In summary, the day-ahead stage solution process of the source–load–storage cooperative optimization model proposed in this paper, which considers two-stage DR and direct purchase of electricity by large consumers, is as follows.

Step 1: Initialize the two-stage optimization model with a lower bound on the runtime gain $LB = -\infty$, an upper bound on the runtime gain $UB = \infty$, an initial number of iterations $M = 1$, and an initial scenario probability distribution P .

Step 2: Solve the master problem to obtain the optimal solution $(x^*, y_0^*, y_k^{m*}, a^T x^* + b^T y_0^* + c^T \xi_0 + \eta^*)$ for the current initial scenario, where $LB = \max\{LB, a^T x^* + b^T y_0^* + c^T \xi_0 + \eta^*\}$.

Step 3: Pass the x^* obtained from the master problem to the sub-problem. Find the worst-case scenario probability distribution P_k^* with known x^* and the optimal objective function value $\eta(x^*)$, when $UB = \min\{UB, a^T x^* + b^T y_0^* + c^T \xi_0 + \eta(x^*)\}$.

Step 4: Given a convergence threshold ε , if $UB - LB \leq \varepsilon$, stop the iteration and return the optimal solution x^* . Otherwise, update the bad scenario probability distribution $p_k^{m+1} = P_k^*, \forall k$ in the master problem.

Step 5: Update $m = m + 1$ and return to step 2.

In summary, the solution process for the source–load–storage synergistic efficiency optimization scheduling model, incorporating two-stage DR and the direct purchase of electricity by large consumers, follows these methodological steps, the solution flowchart is shown in Figure 4.

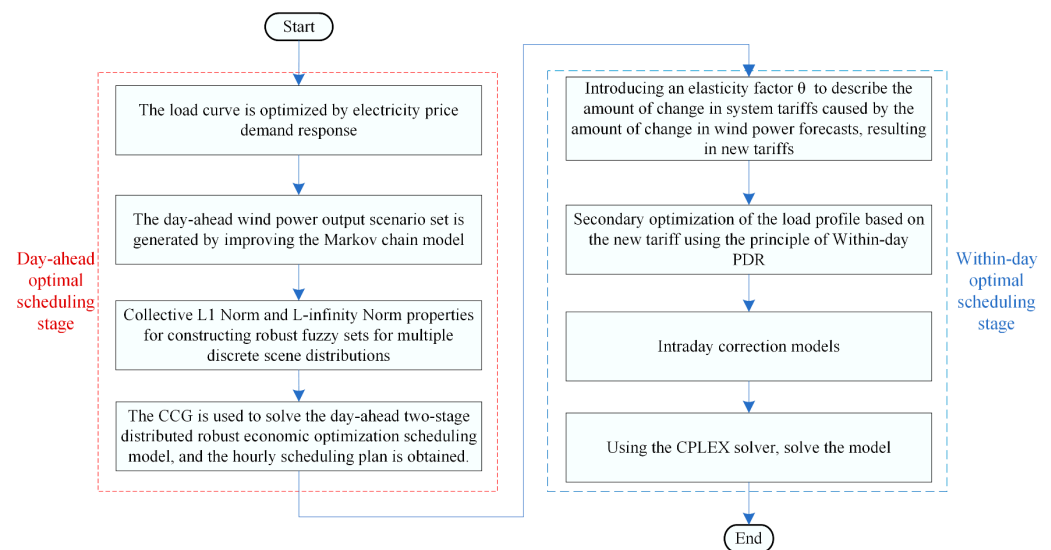


Figure 4. Day-ahead within-day two-phase DR solution flowchart.

Step 1: Optimize the load profile through PDR, strategically modulating electricity consumption in response to price signals and laying the groundwork for subsequent stages of the scheduling process.

Step 2: Construct a fuzzy set using the concepts of the 1 parameter and ∞ parameter to encapsulate the uncertainties. Apply the Column-and-Constraint Generation (CCG) algorithm to solve the day-ahead two-stage distributionally robust economic optimization scheduling model, yielding an hourly scheduling plan accounting for forecasted conditions.

Step 3: Introduce the supply elasticity coefficient E , quantifying the sensitivity of electricity prices to fluctuations in forecasted wind power output. This coefficient guides responsive adjustments in load quantities.

Step 4: Adjust the output of each generation unit and the state of energy storage systems based on forecasted wind power output and load demand. This step ensures that the system's response to intra-day variability is both flexible and robust.

Step 5: Refine the scheduling plan using an intra-day correction model that incorporates real-time data and any deviations from the day-ahead forecasts.

7. Example Analysis

7.1. Setting of Raw Data and Basic Parameters of Unit Combinations

To verify the scheduling model proposed in this paper, the thermal power direct purchase model is used as an example. The six-unit power system provided in [17] is expanded to a twelve-unit system. The system's daily load curve is shown in Figure 5, and unit parameters are shown in Table 1. Additionally, a wind power plant with an installed capacity of 400 MW is introduced to study the impact of direct electricity purchase by large users on the system's wind power consumption capacity. A total of 1000 scenarios were generated and then reduced to 10 by the k-means clustering algorithm. The first type of unit signed a direct purchase of 1600 MW of electricity, while the second type signed for 400 MW. In this paper, the peak shaving capacity is defined as the difference between the system's equivalent load and the minimum total start-up capacity. Thus, the desired peak shaving capacity can be expressed as follows (54).

$$E[tf] = \sum_{k \in K} P_k [\min_{t \in T} (D_t - P_{t,k}^w) - \sum_{i \in N} P_i^{\min}] \quad (54)$$

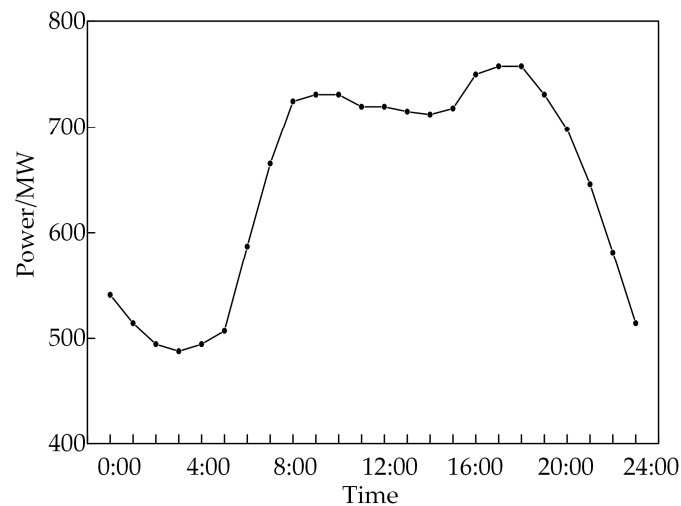


Figure 5. Daily load curve.

Table 1. Unit parameters.

Unit	1	2	3	4	5
$p^{\max}/\text{MW}$	200	80	50	35	40
$p^{\min}/\text{MW}$	50	20	10	10	12
$a/[\$/(\text{MWh})]$	0.035	0.042	0.171	0.016	0.085
$b/[\$/(\text{MWh})]$	29.96	35.23	32.44	40.02	35.01
$c/[(\$/\text{h})]$	75	350	136	500	500
$R^{\text{down}}/(\text{MWh})$	80	40	20	20	25
$R^{\text{up}}/(\text{MWh})$	80	40	20	20	25
$\alpha_c/[\text{kg}/(\text{MW}^2\text{h})]$	0.038	0.059	0.061	0.067	0.085
$\beta_c/[\text{kg}/(\text{MWh})]$	−2.7	−3.9	−3.9	−3.1	−3.4
$\lambda_c/(\text{kg}/\text{h})$	133.4	90.4	82.5	67.3	83.3
$\alpha_s/[10^{-3}\text{kg}/(\text{MW}^2\text{h})]$	0.37	1.7	2.3	4.02	3.8
$\beta_s/[\text{kg}/(\text{MWh})]$	2.1	3.4	3.6	2.9	3.1
$\lambda_s/(\text{kg}/\text{h})$	169.1	111.4	102.5	89.3	103.3

This paper implements a time-of-use (TOU) pricing strategy to determine the revenue from electricity sales on the field side. The strategy divides the 24 h day into three distinct periods, each with different electricity prices reflecting demand patterns and generation costs. Additionally, the direct purchase price is strategically set to incentivize both power generation enterprises and large consumers. This price is hypothesized to be lower than the selling price, ensuring a profit margin for the power generation enterprise. Furthermore, it will be higher than the grid connection price, reducing procurement expenses for large consumers. This dual-pronged approach aims to enhance the financial benefits for the power generation enterprise while alleviating the cost burden on large consumers. For a detailed account of the TOU pricing strategy and the methodology for calculating electricity prices, refer to [35].

7.2. Wind Power Generation

Due to the inherent variability of wind power output forecasts, clustering historical data are necessary to obtain more reliable results. To minimize human intervention, the elbow method is employed to identify the optimal number of clusters, as illustrated in Figure 6.

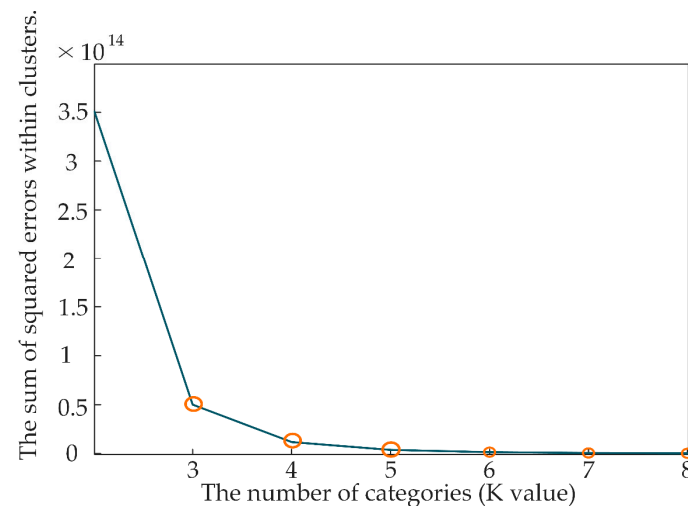


Figure 6. The optimal number of categories by the elbow method.

In this instance, the value of k is set to three for k -means clustering of the historical data set. Subsequently, the non-parametric kernel density estimation technique is employed to fit the prediction error corresponding to the predicted output after clustering. The fitting results are presented in Figure 7.

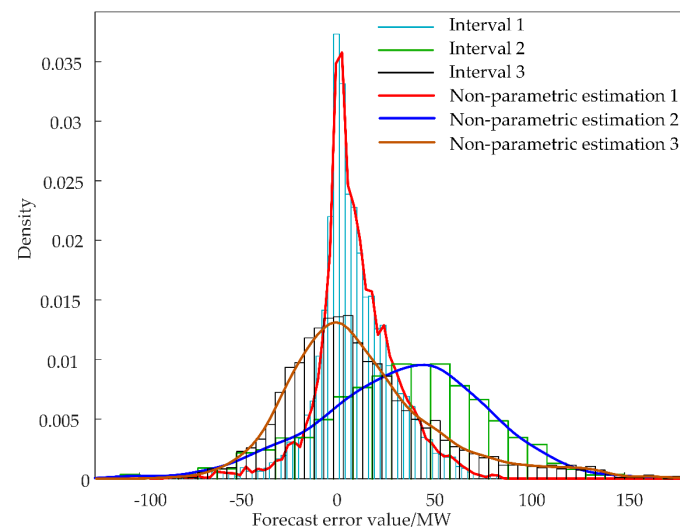


Figure 7. Prediction error distribution fitting graph.

As illustrated in Figure 7, the prediction error distribution after k -means clustering exhibits distinctive characteristics that align with the interval analysis findings. Therefore, it is essential to consider the impact of different prediction values on the probability distribution of the prediction error.

To verify the accuracy of the enhanced Markov chain model proposed in this paper, a comparison with the traditional Markov chain generation scenario is presented in Figure 8.

As illustrated in Figure 8, the enhanced Markov chain model accurately portrays the inherent uncertainty associated with wind power output. It also exhibits a more constrained fluctuation range, especially in the low output range. This suggests that distinct prediction values correspond to specific fluctuation domains and that there is no discernible disordered fluctuation. In conclusion, the enhanced Markov chain model proposed in this paper effectively reflects the interval and time series characteristics of wind power output. The wind power output scenarios, condensed using an enhanced

Markov chain model, are illustrated in Figure 9. The associated probabilities for these scenarios are detailed in Table 2.

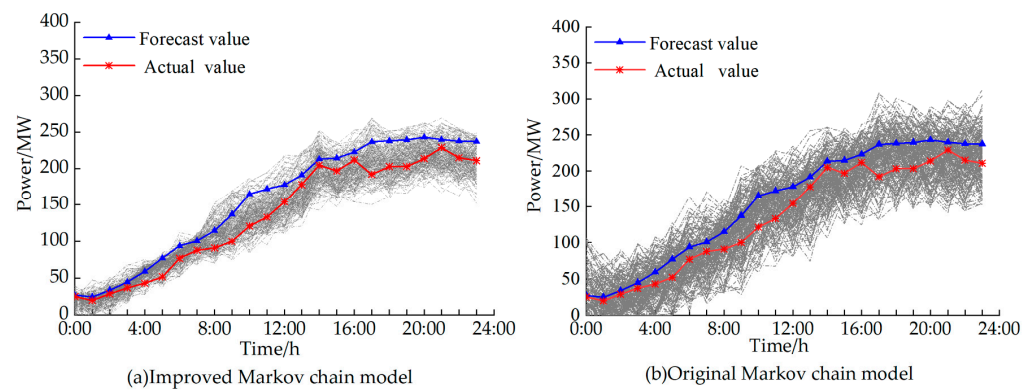


Figure 8. The wind power scenario set is compared as follows: (a) the improved Markov chain model and (b) the original Markov chain model.

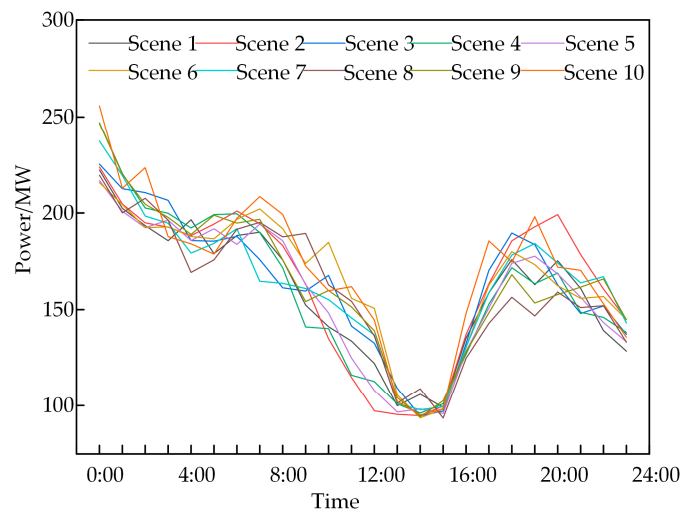


Figure 9. Wind power is predicted for each scenario.

Table 2. Probability of each scenario.

Scene	1	2	3	4	5	6	7	8	9	10
Probability	10%	20%	15%	5%	13%	7%	6%	4%	12%	8%

7.3. Comparison of Results for Different Confidence Intervals

To demonstrate the effectiveness of the robust optimization model for two-stage DR distribution under the comprehensive norm constraint, as introduced in this paper, an example is provided using the direct purchase of electricity price model. The electricity prices are specified as follows: a valley electricity price of USD 53.85/MWh, a flat electricity price of USD 89.23/MWh, and a peak electricity price of USD 126.15/MWh. This analysis considers the inherent uncertainty of wind power and examines the impact of different confidence intervals, denoted as α_1 and α_∞ , on the direct purchase system for large users. The outcomes of the system benefits, evaluated under these varying confidence intervals, are presented in Table 3.

Table 3. Comparison of system returns under different confidence levels.

α_1	Income/USD 10 ⁶		
	$\alpha_\infty = 0.5$	$\alpha_\infty = 0.8$	$\alpha_\infty = 0.99$
0.2	9.1676	9.1673	9.1670
0.5	9.1674	9.1671	9.1668
0.99	9.1674	9.1667	9.1662

Table 3 demonstrates the relationship between system benefits and the confidence levels of the probability distribution. Specifically, when α_1 is held constant, the system benefit is observed to decrease as α_∞ is held constant, and the system benefit declines as α_1 increases. This behavior reflects the trade-off between confidence in the wind power output forecast and the economic performance of the system. Furthermore, Equation (45) reveals that as the confidence levels of the probability distribution values for wind power output increase, the confidence interval for the system's performance metrics also expands. This enlargement signifies an increased level of uncertainty in wind power output, necessitating the derivation of a decision-making plan under more adverse conditions. As a result, the system incurs higher costs and realizes lower benefits. The findings from Table 3 and the analysis of Equation (45) collectively underscore the robustness of the proposed model. They validate the model's capacity to accommodate varying levels of uncertainty and its applicability for further research and practical implementation in the context of two-stage DR distribution.

To further validate the merits of the comprehensive norm approach, this study conducts a comparative analysis with the individual L1 norm and L-infinity norm. Initially, the total system benefit is determined under the condition that the single L-infinity norm is set to 0.99. Subsequently, this outcome is compared with scenarios where the L-infinity norm remains constant at 0.99 while the L1 norm is varied. The comparative results are presented in Table 4.

Table 4. Comparison between the comprehensive norm and the singular L-infinity norm.

α_1	Income/USD 10 ⁶	
	Comprehensive Norm	L-Infinity Norm
0.2	9.1670	9.1652
0.5	9.1668	9.1652
0.99	9.1662	9.1652

In a parallel approach to our analysis, the total system benefit is initially calculated with a single L1-norm set at 0.5. Subsequently, a comparative assessment is conducted by keeping the L1-norm constant at 0.5 while varying the L-infinity norm. The outcomes of this comparative analysis are detailed in Table 5.

Table 5. Comparison between the comprehensive norm and the singular L1-norm.

α_∞	Income/USD 10 ⁶	
	Comprehensive Norm	L1-Norm
0.5	9.1674	9.0656
0.8	9.1671	9.0656
0.99	9.1668	9.0656

An examination of Tables 4 and 5 reveals that the total system benefit, when derived under the comprehensive norm, surpasses that achieved with the sole application of either the L1-norm or the L-infinity norm. This observation suggests that the comprehensive

norm, compared to the individual norms, exhibits a reduced level of conservatism and thus offers greater economic efficiency.

7.4. Impact of Two-Stage Demand Response on Wind Power Consumption

Peak shaving capacity is a critical parameter that defines the system's ability to accommodate wind power. This paper explores the concept of enhancing wind power consumption capacity via a two-stage DR mechanism. To achieve this, we employ a synergistic optimization model of source–load–storage that incorporates intra-day rolling optimization as a case study. The analysis is structured around the merits of the DR and the effectiveness of intra-day rolling adjustments. For a comprehensive evaluation, three distinct scenarios have been devised and are presented in Table 6. These scenarios provide a comparative framework to assess the impact of different dispatch schemes on the system's performance. Furthermore, Figure 10 offers a visual representation of the distribution of direct purchase electricity across the various dispatch schemes, highlighting the differences in wind power integration and consumption capacity under each scenario.

Table 6. Example simulation and comparison scheme.

Scenario	Dispatch Plan
1	Optimized scheduling (large users + energy storage + DRO)
2	Day-ahead optimization scheduling + day-ahead DR + within-day rolling optimization
3	Day-ahead optimization + two-stage DR + within-day rolling optimization

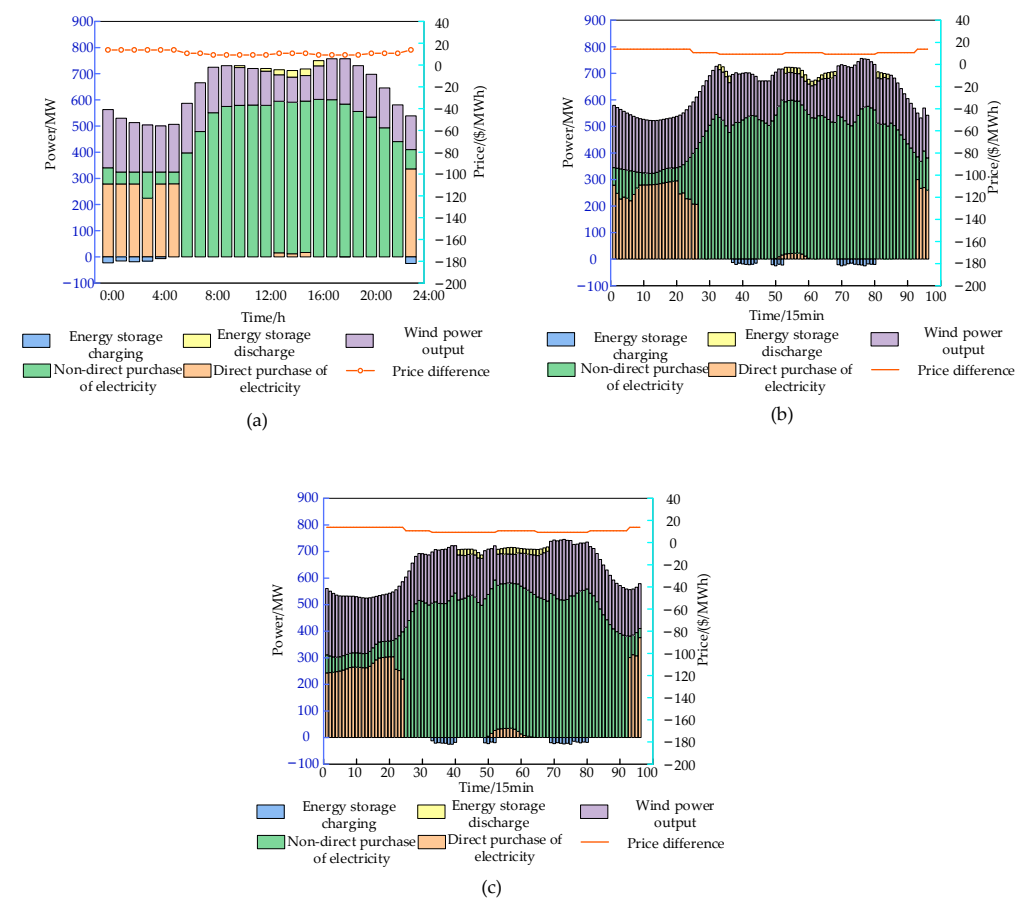


Figure 10. Wind power is predicted for each scenario, as (a) shows Scenario 1, (b) shows Scenario 2, and (c) shows Scenario 3.

Figure 10 provides a comparative analysis of the load curve's peak–valley difference following the implementation of daily DR measures. Panels (a) and (b) demonstrate

that while the peak–valley difference is reduced, significant fluctuations occur during the transitional periods between peak and valley loads. This is attributed to the time-of-use tariff, which causes load variations to respond solely to price signals rather than the base load. Panels (b) and (c) further illustrate that with the intra-day wind power output deviation-guided electricity price, the peak–valley difference is minimized even more. Additionally, the output curve of the thermal power unit exhibits a smoother trajectory, indicating an increased consumption of wind power. This suggests that the intra-day wind power output deviation-guided electricity price DR model can rapidly adapt to real-time fluctuations in wind power output, ensuring the robustness and economic efficiency of the dispatch plan. To provide a more nuanced understanding of the impact of two-stage DR and direct power purchase transactions on the system’s peak shaving capacity, Figure 10 presents three distinct scenarios. The total expected revenue and the system’s peak shaving capacity, as influenced by these scenarios, are detailed in Table 7.

Table 7. Comparison of the scenario scheduling results.

Scenario	Total Income/USD 10 ⁵	Peak Shaving Capacity/MW	Wind Power Consumption/MW	Wind Power Consumption Rate/%
1	9.1663	195.3580	3791.27	78.67
2	9.2103	203.74	4225.51	87.68
3	9.3203	194.13	4366.13	91.45

Figure 11 delineates the unit start-up status across the three scenarios under consideration. The integration of a two-stage DR model leads to a more optimized scheduling of thermal power unit operations, characterized by a reduced frequency of start-ups and shutdowns. Specifically, in Scenario 3, Unit 6 remains active throughout the dispatch period, minimizing the necessity for start–stop cycles. A notable observation in Figure 11c is that Unit 8 remains offline in Scenario 3. This can be attributed to the smoother load curve achieved through the two-stage DR adjustments, which have led to an increased consumption of wind power and a consequent decrease in both the net load demand and the system’s reserve capacity requirements. Table 7 presents a quantitative assessment of the impact of the DR on the power generation enterprise’s revenue and wind power consumption. The data indicate a positive trend in both metrics following the implementation of DR measures. Although Scenario 3 exhibits a lower peak shaving capacity compared to Scenarios 1 and 2, it yields superior economic outcomes by accepting a trade-off in peak shaving capacity. In conclusion, the two-stage DR model proposed herein demonstrates efficacy in mitigating the peak–valley disparity of the demand curve, smoothing the load profile, diminishing the operational start–stop adjustments for generator units, and curtailing the dispatch costs of the power system.

To more meticulously demonstrate the advantages and disadvantages of DROS, we have compared its results with those of stochastic optimization and robust optimization, as detailed in Table 8.

As can be seen from the calculation results in Table 8, stochastic optimization is found in three scenarios. Although the total revenue is always higher than that of other methods, the peak regulation capacity is lower than that of other methods, and the maximum difference in peak regulation capacity is 44.1184 MW. Robust optimization has a higher peak regulation capacity than other methods, but the total revenue is lower than that of DROS, and the maximum difference in revenue compared to DROS is USD 14,460. The total benefit of the DROS and the peak regulation capacity are between those of stochastic programming and robust methods, indicating that the DROS algorithm used in this paper is more robust than stochastic programming and more economical than robust optimization. Combining the economy of stochastic programming with the robustness of robust optimization, the DROS proposed in this paper has achieved a balance between economy and robustness.

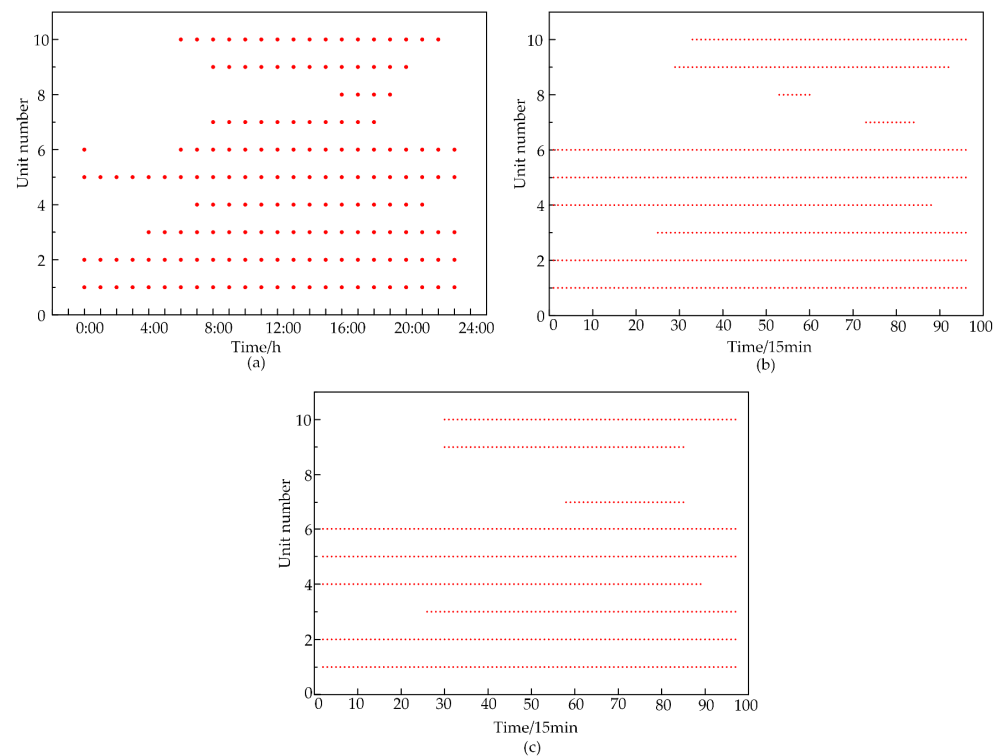


Figure 11. System unit startup status for each scenario: (a) shows Scenario 1, (b) shows Scenario 2, and (c) shows Scenario 3.

Table 8. Comparison of optimization method scheduling results.

Scenarios	Stochastic Optimization		Robust Optimization		DROS	
	Total Income/USD 10^5	Peak Shaving Capacity/MW	Total Income/USD 10^5	Peak Shaving Capacity/MW	Total Income/USD 10^5	Peak Shaving Capacity/MW
1	9.386	187.0663	9.0217	227.9147	9.1663	195.3580
2	9.4481	173.8063	9.1823	217.9247	9.2103	203.74
3	9.5039	169.2263	9.2378	203.9147	9.3203	194.13

8. Conclusions

This paper introduces an enhanced Markov chain model designed to generate a spectrum of wind farm output scenarios that encapsulate the inherent uncertainty of wind power generation. To address this uncertainty, we employ a two-stage distributed robust optimization scheduling model. This model serves as a framework for analyzing the system's wind power consumption capacity, particularly focusing on the effects of two-stage DR mechanisms and the direct purchase of electricity by large consumers. The conclusions are as follows.

(1) Our study successfully introduces an enhanced Markov chain model that captures the temporal and interval characteristics of wind power prediction errors. This model significantly improves the accuracy of wind power scenario generation, which is crucial for integrating wind power into the power system. Future work could focus on further refining this model by incorporating additional meteorological data and machine learning techniques to predict wind power output with even greater precision.

(2) The incorporation of DR principles at the day-ahead dispatch stage has yielded significant improvements over the traditional approach, which solely relied on day-ahead optimization dispatch. Specifically, the revenue generated by the power system has increased by USD 4400, the peak shaving capacity has expanded by 8.382 MW, and the

consumption of wind power has risen by 434.24 MW. Moreover, the rate of wind power consumption has experienced a notable increase, reaching 9.01%. These empirical results substantiate the effectiveness of the DR in modulating electricity demand on the load side, attenuating the peak–valley disparity, and augmenting wind power utilization. Concurrently, the economic dispatch of the power system has been enhanced, demonstrating the tangible benefits of integrating DR mechanisms into power system operations; future research will explore combining the DR with other forms of renewable energy, such as solar energy, to further optimize the energy mix and system reliability.

(3) The present study conducts a meticulous comparison between the short-term forecasted output and the scheduled output of wind power, enabling the precise calculation of the within-day wind power output deviation. Utilizing this deviation, dynamic adjustments to electricity prices and optimizations of load curves are implemented. These actions, within the framework of a two-stage DR, have resulted in a marked increase in the total revenue from day-ahead optimization dispatch, amounting to USD 15,400. Concurrently, there has been a significant boost in wind power consumption, totaling 574.86 MW, and an elevation in the wind power consumption rate to 12.7%. Furthermore, the analysis reveals an 8% escalation in the total revenue attributable to DR on the preceding day. Despite a 9.61 MW reduction in peak shaving capacity, there has been a notable increase in wind power consumption by 140.62 MW, and the consumption rate has risen by 3.77%. To ensure the safe and stable operation of the power system, a strategic sacrifice of a portion of the peak shaving capacity is made. This decision furthers the objective of increasing wind power consumption and mitigates the output adjustments required from thermal power units and energy storage systems; while our DROS model has shown promising results, there are several areas for future exploration. These include the application of the model to different geographical regions with varying wind power characteristics, the integration of energy storage systems to further enhance the system's flexibility, and the development of more sophisticated user response models to capture the complex dynamics of consumer behavior in response to DR signals.

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